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Determining Depot Locations and Capacities for Demand Responsive Autonomous Vehicles

수요응답형 자율주행차의 **Depot** 입지 및 용량 결정

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Abstract

In the automobile and transportation sector, various technologies related to an autonomous vehicle (AV) and shared mobility are expected to upgrade. Accordingly, various types of service using AV have been proposed recently in the field of Demand Responsive Transport (DRT) such as a shared autonomous vehicle (SAV), which is one-way car sharing services using AV. The Demand Responsive Autonomous Vehicle (DRAV) system is a system that utilizes AV for on-demand service in the public domain. It can improve the travel conveniences for users in blind spot of transport service areas and vulnerable road users (e.g. disabled, elderly). Additionally, since this system also is used as a demand management policy by promoting the sharing transport, DRAV can be considered as a competitive new para-transit option. However, although many previous studies are concerned about road congestion possibly caused by a large number of AV, lack of studied considered such problem. DRAV depot not only decreases the road congestion but also plays multiple roles such as effective vehicle management and charging infrastructure of future rechargeable battery vehicles.

This study aims to develop a model and an algorithm to determine optimal location, quantity, and capacity of DRAV depot considering road congestion due to empty AV travels after the introduction of the system. Iterative modal split and traffic assignment procedures are deployed in the model to describe user's behavior more realistically.

Moreover, a solution algorithm based on genetic algorithm (GA), a representative meta-heuristic technique, is developed to solve the NP-hard combinatorial optimal solution problem type in a reasonable time. The characteristic of the problem that the solution pattern varies according to the number of depots is considered in the algorithm. EMME4, a typical transportation simulation program, and python 2.7 are utilized for efficient analysis and the problem-solving process is automated by using application programming interface (API).

The Mandl's network is selected for a case study analysis. Results reveals that network congestion cost due to empty vehicle travel should be considered in the DRAV depot decision process. Depot location is determined by high DRAV demand, but the additional construction of depot is recommended for highly congested areas to reduce the congestion cost. Further scenario analyses, represents the various future situations, proves that influencing factors for the depot location selections such as local transportation environment and location-related factors (e.g, traffic volume, travel pattern, public transport route, land cost) for location selections should be fully considered.

Keywords: Demand responsive autonomous vehicle (DRAV),
Location and capacity of depot, Bi-level model,
Genetic algorithm (GA)
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1. Introduction

1.1. Research Background and Objective

The main issues in the future transportation and automobile industry that are being discussed are autonomous vehicles (AV), connected vehicles, wireless charging technology, and the shared mobility. In particular, many technology investments and business cooperations are being made both domestically and abroad regarding AV. According to Korean Automobile Regulations Act (2015), AV is defined as automobiles that can be driven by the automobile without any manipulation of drivers or passengers. The automation level is divided into five to six levels by the driver's intervention according to the US NHTSA and SAE (2015) as shown in table 1-1, and it is predicted that self-driving vehicles of level 4 or higher will be commercialized after 2025.

There are various views on AV. Numerous research results or experts argue that the mechanized reaction time of autonomous vehicles can increase the efficiency of road operation in a connected vehicle environment. It can also reduce the accident rate by mechanically replacing the human factors that occupy more than 90% of current accidents, and it can improve the mobility of people with disabilities such as disabled people and the elderly who are hard to drive. Vehicle ownership is also reduced in the future, which is a positive aspect of traffic congestion management. However, there are many opinions that it is possible to increase the congestion on the road due to the empty vehicle travel when introducing taxi and sharing service using AV. There are also some issues that need to be addressed before introducing AV at this time, such as unclear responsibilities, system errors, hacking possibility, and related laws and regulations.

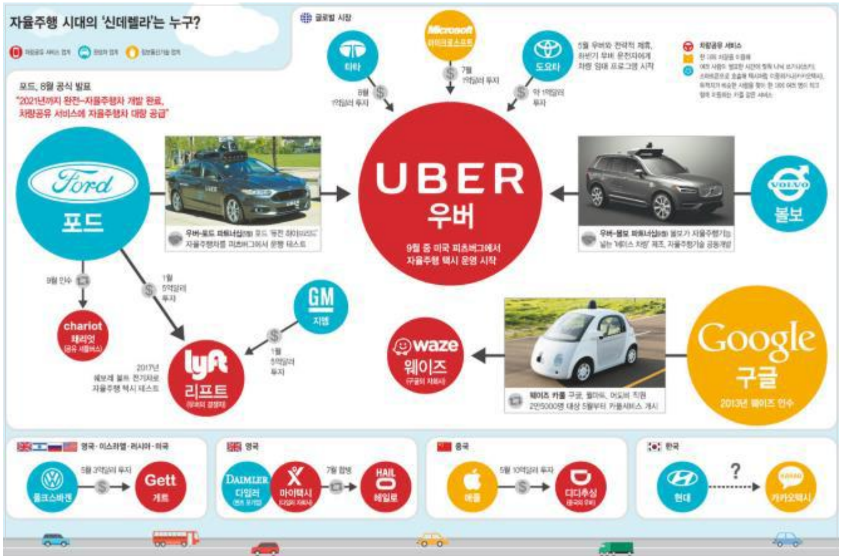
<Table 1-1> Level of Autonomous Vehicle

SAE		Steering and Acceleration/ Deceleration	Monitoring and traffic environment	Failure response	NHTSA	
level	Definition				level	Definition
0	No Automation	Driver	Driver	Driver	0	No Automation
1	Driver Assistance	Driver	Driver	Driver	1	Function Specific Automation
2	Partial Automation	AI System	Driver	Driver	2	Combined Function Automation
3	Conditional Automation	AI System	AI System	Driver	3	Limited Self-Driving Automation
4	High Automation	AI System	AI System	AI System	4	Full Self-Driving Automation
5	Full Automation	AI System	AI System	AI System		

Source: Taxonomy and definition for terms related to on-road motor vehicle automated driving systems (SAE, 2016)

Although the perception of AV is so diverse, the market outlook for AV is positive. According to VTPI, AV will start commercialization in 2020 and account for more than 30% of all vehicles and more than 50% of new vehicles by 2040. Besides, IT companies such as Google, Apple and NDVIA, shared transportation companies such as Uber and Lyft, and automobile manufacturers such as Ford, BMW and

Hyundai/Kia are working together to develop the AV industry.

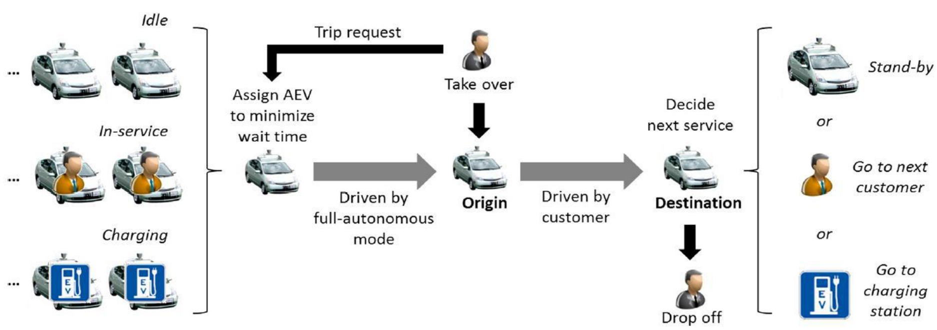


[Figure 1-1] Business alliance with vehicle-car industry

Concerning to the domestic policies related to AV, the Ministry of Land, Transport and Maritime Affairs has provided various technical and institutional support such as enactment of laws related to AV and issuance of provisional permission for AV with the purpose of technology commercialization by 2020. By May 2017, total 19 domestic institutions in industrial and academic sectors have developed AV technology with the provisional permission, which is first introduced in February 2016.

Shared Economy is defined as an economic activity in which the utilization of idle resources owned by an individual or a company is easily carried out through the market. It is possible to utilize efficiently at low cost without owning rare resources, and a shared economy is being made in various areas such as accommodation (Airbnb), marketplace (TaskRabbit), car sharing (Lyft, Car2go) and mobility service platform(Uber). The shared economy in the transportation sector, shared mobility, includes car sharing, ride sharing, bike sharing, and shared parking. Shared mobility has been studied to helpful for managing traffic demand, saving energy and reducing GHG through reduction of vehicle ownership. As a result, the industries and markets related to shared mobility have been continuously expanded, and this trend is expected to increase further in the future.

As the AV technology and the shared mobility industry are expanding, new services using AV for on-demand service are attracting attention. SAV (Shared Autonomous Vehicle), which is one-way car sharing service with AV, is a representative example. There are already several studies concerning the operation strategy and depot location of SAV, and many vehicle companies have invested with an interest in SAV. The service type is configured such that, when a user requests service, the AV itself reaches the user's departure location and travels to the user's destination, and then travels to the destination of the AV itself.



[Figure 1-2] Service concept of SAV (Kang. 2017)

However, deep consideration of this type of service in the public domain is hard to find. Therefore, this study defined DRAV (Demand Responsive Autonomous Vehicle) as an AV providing on-demand and one-way transportation service in the public domain. The differences of DRAV compared with other types of vehicles related to autonomous driving and shared mobility is summarized as follows.

<Table 1-2> Comparison of DRAV with other types of vehicles

Category	Meaning (or example)	Route	Vehicle ownership	Operator
AGT	Automated Guideway Transit	Fixed	Public	Public
Autonomous taxi	Driverless taxi, Robo-taxi, Robo-cab	Non-fixed	Personal or private	Private
Ride sharing	Carpool, Vanpool	Non-fixed	Personal	Private
Ride hailing	TNC[1] (Uber, Lyft)	Non-fixed	Personal or private	Private
SAV	Shared Autonomous Vehicle	Non-fixed	Private	Private
DRAV	Demand Responsive Autonomous Vehicle	Non-fixed	Public	Public

1) TNC(Transport Network Company)

As a future para-transit, the necessity of DRAV introduction in the public domain is as follows. First of all, the DRAV system using self-driving vehicle can improve the mobility of traffic disadvantaged people such as traffic blind zone users, the disabled, and the elderly because it has the time and space fluidity of services that do not have specific routes and service traffic. Besides, since there is no need for drivers in the system, the operational efficiency can be increased in the long run. Especially, it is competitive against the non-profit buses operated by subsidy support from the municipality. Moreover, it can be utilized as a demand management policy through activation of shared traffic. For example, it can create various social benefits such as energy saving and reduce emission gas in connection with ride sharing.

However, when introducing a DRAV system in the public sector, consideration of additional road congestion due to empty vehicle travel is necessary as many AV-related studies have pointed out. Installation exclusive depot for DRAV is one solution for the congestion. The depot can not only induce the empty vehicle travel of AV on the road, but it is also necessary for the following aspects. Firstly, infrastructure for charging is needed when utilizing future cars such as electric cars (EV) and hydrogen battery cars for services. Currently, the technology of AV self-charging using the electronic panel is completed. Therefore, DRAV system can be operated by installing the self-charging infrastructure in the depot, which is indispensable for using EVs and hydrogen battery cars. Secondly, efficient management of the vehicle is possible through the exclusive depot for DRAV. The present one-way car sharing is operated by placing a small number of vehicles at multiple locations because the users must move to the location of the vehicle, but the difficulty of managing the vehicle is pointed out as a problem. The DRAV system, which does not require the user to move to the service vehicle, can efficiently manage the vehicle through the depot installation. Finally, it is necessary to install the depot when considering the poor parking environment in Korea. Some overseas one-way car sharing such as Car2go is providing services by using roadside parking facilities. However, it is difficult to utilize the parking facilities when considering the domestic conditions where the parking space is narrow and the parking ratio is high, so depot installation is required.

The purpose of this study is to develop a model that determines the optimal DRAV depot location, quantity, and capacity. To find out the optimal solution, costs for both user and operator that may arise from the introduction of the system is taken into account based on bi-level modeling. In the model, network congestion due to empty vehicle travel between origin or destination of DRAV users and depot is reflected, which is not considered in the previous study. Furthermore, mode choice and traffic assignment process are iteratively contained in the model for reflecting more realistic user movement behavior. A meta-heuristic algorithm based on genetic algorithm(GA) is developed to solve the NP-hard problem within a reasonable time. Finally, the optimal depot location, quantity, and capacity change according to various scenarios according to possible future environmental change are analyzed.

1.2. Research Flow

The purpose of this study is to develop a model for DRAV depot location, quantity, and capacity determination, and to develop algorithms for solving this problem. The overall procedure for this is shown in Fig. 1-3. Each chapter covers the following contents.

In chapter 2, literature review is conducted to set the direction of model and algorithm development. First of all, review of latest DRAV related research trends is conducted through literature review concerning SAV. Also, previous studies concerning location model in shared mobility are reviewed to look at the structure of the model. Besides, GA and GA-related researches, which is the basis of the algorithm in this study, are also reviewed. Finally, the differences from the existing studies are summarized, and the improvement direction of this research is present.

Chapter 3 builds a model for DRAV Depot location and capacity determination. The structure of the model is bi-level programming type which is mainly used in the transportation network design problem. It determines the depot location, quantity, and capacity from the policy maker's point of view in the upper model. The behavior of the user by the decision of upper model is described in the lower model. In the upper model, the purpose is to minimize the total cost of the user and the operator side. Generation of empty vehicle travel, traffic volume conservation, depot capacity and service level are considered as constraints of the model. In the lower model, a user equilibrium(UE) assignment model, which all users travel for minimizing their travel time, is adopted for passenger cars and AVs, whereas an optimal strategy assignment model is applied for bus users to select a route that minimizes their travel time considering waiting time.

In chapter 4, the algorithm for solving the model is developed. Since the problem in this study is combinatorial optimization problem which is known as the NP-hard problem, the meta-heuristic method is adopted for solving the problem in polynomial time. This study presents a solution method based on genetic algorithm, which is a typical meta-heuristic algorithm. The algorithm is constructed to consider the characteristics of this problem that various local optima exist due to different solution patterns according to the number of depots.

In chapter 5, GA parameter tests are conducted through a case study using Mandl's network, and the adequacy of developed model and algorithm is verified. Then, several scenario analyses are performed considering various situations at the time of introduction of DRAV, and the changes of depot location, quantity, and capacity of each scenario are analyzed. Moreover, the practical application of the developed model is verified through the large-scale network analysis.

Finally, chapter 6 reveals the implications of the policy and implications of the research through the analysis results and suggests future direction of the study.

Literature Review	• Research trends related to DRAV • Location model in shared mobility • Genetic algorithm
Model Formulation	• Definition of objective function, constraints and decision variables (Bi-level) - Upper : Determination of the location, quantity and capacity of DRAV station - Lower : Modal split and multi-class assignment considering empty vehicle travel
Algorithm Development	• Development of algorithm flow based on GA • Implementation of algorithm (Python 2.7, EMME 4)
Analysis	• Case study : Mandl's network(15 nodes, 44 links, 4 Transit lines) • Scenario analysis : Changes in the surrounding environment • Large-scale network analysis
Conclusion	• Conclusion and future research

[Figure 1-3] Research flow

2. Literature Review

The purpose of the literature review is to examine the research trends related to DRAV and to find out implications that can be referred to the models and algorithms developed in the present study. To this end, it is first provided the research trends related to shared mobility including SAV. Then, the points to be referred to in model construction are identified through reviewing previous research on location models in transportation such as FCLM. Besides, the points to be considered in the algorithm of this study are discussed through theoretical considerations and examination of previous studies concerning GA. Finally, based on the results of these literature reviews, the limitations and improvements are presented.

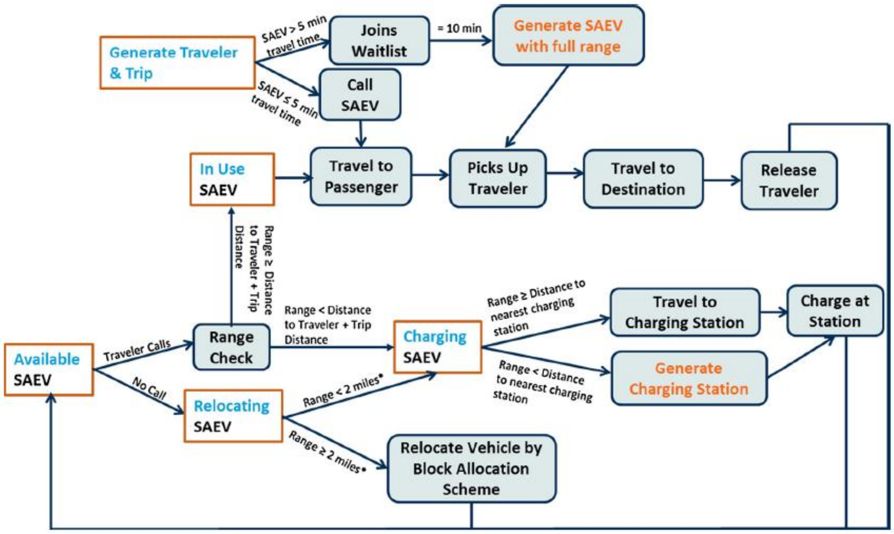
2.1. Research Trends Related to DRAV

Recent studies related to DRAV have been on the subject of SAV since 2014. The research area has been mainly focused on the mode choice and the effect on the introduction of the system. In most studies, it is analyzed that the system is positive regarding energy savings and reduction of emission through replacement of existing vehicles, and it is also evaluated to have competitiveness regarding modal share.

Fagnant and Kockelman (2014) studied on the environmental benefits of SAV through many case-study applications based on an agent-based model. In the study, they provided trip generation and trip distribution model using national household travel survey. They resulted out that each SAV can replace around eleven conventional vehicles, but adds up to 10% more travel distance than comparable non-SAV trips, resulting in overall beneficial emissions impacts, once fleet-efficiency changes and embodied versus in-use emissions are assessed.

Chen et al. (2016) developed discrete-time agent-based model for determining the location of charging station for SAEV(Shared Autonomous Electric Vehicle) and optimal fleet size. In their model, the location of charging station and fleet size is determined separately in 2 phase structures. The network is divided into 160,000 quarter-mile by quarter-mile cells, and the location of charging station is installed in a cell where the vehicle cannot travel to the nearest charging station with the remaining charge. The fleet size is decided for meeting the demand based on the historical data, and it is independent of the location of charging station.

Chen's follow-up study has been conducted on mode share under various pricing schemes. Multinomial logit model in an agent-based framework is employed as mode choice model and SAEVs are priced between $0.75 and $1.00 per mile. As a result of analysis for the mid-sized city, mode share of SAEV is predicted to lie between 14 and 39%, when competing against privately-owned, manually-driven vehicles and city bus service.

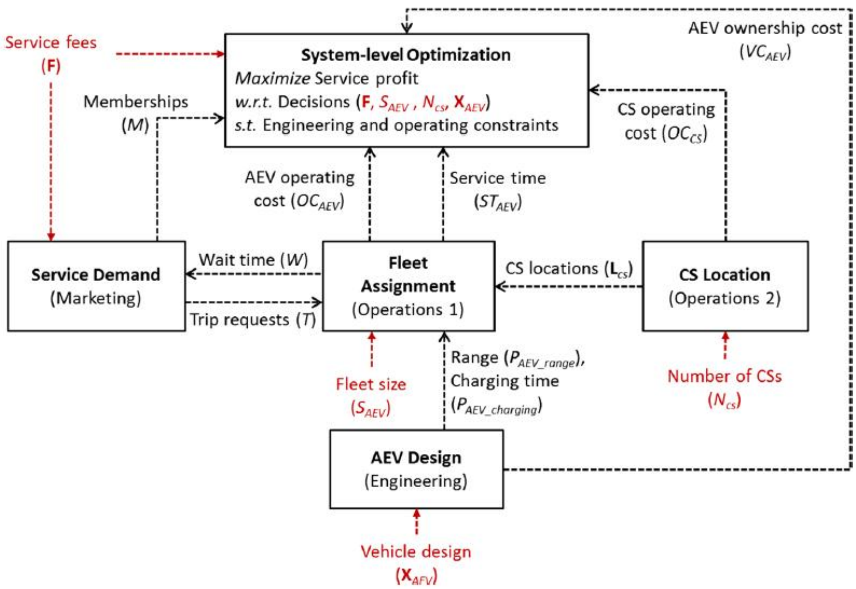


[Figure 2-1] Algorithm flow of charging station generation (Chen et al. (2016))

The OECD/ITF (2016) conducted a study on the vehicle ownership that can be substituted by SAV and its effect on emission for Lisbon, Portugal. The study suggests that replacing all trips with SAV can reduce the emission level by 30%. Furthermore, total fleet size of SAV can be 3% of the current privately-owned vehicles and buses.

There are some survey results concerning the preference of SAV. Krueger et al. (2016) presented participants a choice between their current mode of public transportation and SAV alternative based on hypothetical cost, travel time, and wait times based on survey. As a result for participants from major Australian cities, it is revealed that wait times affect the propensity of switching to SAV significantly, while marginal increases in cost affect the likelihood of using the pooled SAV. Another survey found complementary results by Bansl et al. (2016). In their research, full-time male workers are likely to use SAV more frequently, while licensed drivers are less likely to use them. And people who are familiar with advanced transportation systems such as Goole's self-driving car and the anti-loc braking system is more likely to use SAV.

Kang et al. (2017) designed SAEV for maximizing profit from the view of operator. The design framework consisted of four sub-system models, that are the fleet assignment, charging station location, AV design, and service demand. And system-level profit-optimization model integrates all of them in his study. By comparing the result of AV using the electric engine with that of the gasoline engine, they showed that AV using the electric engine was more sustainable and profitable than the one using the gasoline engine.



[Figure 2-2] System design framework (Kang et al. (2017))

Chen et al. (2017) present an ensemble learning approach for better understanding ride splitting behavior of passengers of ridesourcing companies who provide prearranged and on-demand transportation services. To improve the prediction accuracy of ride splitting choices, real-world individual-level data from on-demand service platform of DiDi, China is used. They insist that ensemble is particularly useful and powerful in the ride splitting analysis and outperforms other widely used classifiers such as logistic regression, SVM, and naive Bayes classification.

2.2. Location Model in Shared Mobility

2.2.1. Location model of one-way car sharing

DRAV is similar to one-way car sharing in the aspect that the origin and destination of service vehicle are different. Therefore the review of one-way car sharing research can be helpful to construct the model of DRAV.

Correia and Antunes (2012) developed optimization model for one-way car sharing vehicle depot locations and the number of parking spaces. The objective function is to maximize the profit(Π) of the operating agency, taking into account the revenues generated by the system, the depot maintenance cost, and maintenance, relocation, depreciation costs for the vehicles. The model developed by Correa and Antunes (2012) is as follows.

$$Max.\, \Pi = (P - C_{m1}) \times \sum_{i_t j_{t+\delta_{ij}^t} \in A_1} D_{i_t j_{t+\delta_{ij}^t}} - C_r \sum_{ij \in A_3} \delta_{ij}^T R_{ij} - C_{m2} \sum_{i \in N} Z_i - C_\nu \sum_{iINN} V_{i_1}$$

subject to,

$$V_{i_t} = V_{i_{t-1}} - \sum_{j_t \in X} D_{i_{t-1} j_{t-1+\delta_{ij}^t}} + \sum_{j_t \in X} D_{j_{t-\delta_{ji}^t} i_t} \quad \forall i_t \in X$$

$$S_{i_t i_{t+1}} = V_{i_t} - \sum_{j_t \in X} D_{i_t j_{t+\delta_{ij}^t}} \quad \forall i_t \in X$$

$$V_{i_t} = V_{i_T} + \sum_{j \in N} R_{ji} - \sum_{j \in N} R_{ij} \quad \forall i \in N$$

$$\sum_{j \in N} R_{ij} \le V_{i_T} \quad \forall i \in N$$

$$Z_i \ge V_{i_t} \quad \forall i_t \in X$$

$$V_{i_t} \le M \times Y_i \quad \forall i_t \in V$$

$$Y_i \le Z_i \quad \forall i \in N$$

$$D_{i_t j_{t+\delta_{ij}}} \le Q_{i_t j}^P \quad \forall i_t, j_t \in X$$

$$\sum_{i \in N} Y_i \le N_{\max}$$

$$\sum_{i_t j_{t+\delta_{ij}^t} \in A_1} D_{i_t j_{t+\delta_{ij}^t}} \Big/ \sum_{i_t \in X,\, j \in N} Q_{i_t j}^P \ge Q_{\min}$$

$$D_{i_t j_{t+\delta_{ij}^t}} \ge 0 \quad \forall (i_t, j_{t+\delta_{ij}^t}) \in A_1$$

$$R_{ij} \ge 0 \quad \forall (i,j) \in A_3$$

$$Z_i \ge 0 \quad \forall i \in N$$

$$V_{i_t} \ge 0 \quad \forall i_t \in X$$

$$S_{i_t j_{t+1}} \ge 0 \quad \forall (i_t, j_{t+1}) \in A_2$$

$$Y_i = (0,1) \quad \forall i \in N$$

where,

- N = {1,...,i,...N} : set of candidate sites for the location of depots
- T = {1,...,t,...,T} : set of time steps in the operation period
- X = $\{1_1,\ldots,i_{t-1},i_t,i_{t+1},\ldots,N_T\}$: set of nodes of a time-space network combining the N candidate sites with the T time steps (i_t represents candidate site i at time step t)
- A_1 = $\{\ldots,a_1(i_t, i_t+\delta_{ij}^t),\ldots\}$, $i_t \in X$: set of arcs that represent the movement of vehicles between depots i and j, $\forall i,j \in N$, i$\neq$j between time steps t and $t+\delta_{ij}^t$, where δ_{ij}^t is the travel time between depots i and j when the trip starts at time step t
- A_2 = $\{\ldots,a_2(i_t, i_{t+1}),\ldots\}$, $i_t \in X$: set of arcs that represent vehicles stocked in depot i, $\forall i \in N$, from time step t to time step t+1
- A_3 = $\{\ldots,a_2(i_T, i_1),\ldots\}$, $i_T \in X$: set of arcs that represent relocation operations from depot i to depot j, $\forall i,j \in N$, i$\neq$j, at the end of operation period (time step T)
- $D_{i_t j_{t+\delta_{ij}}}$: number of vehicles used between depots i and j from time step t to $t+\delta_{ij}^t$
- R_{ij} = {1,...,i,...N} : number of vehicles relocated between depot i and j after the operation period
- Z_i = {1,...,i,...N} : size of depot i
- V_{i_t} = {1,...,i,...N} : number of available vehicles at depot i in time step t
- $S_{i_t i_{t+1}}$ = {1,...,i,...N} : number of vehicles stocked at each depot i

from time step t to t+1;

- Y_i = 1 if a depot is located at candidate site i, otherwise 0.
- P : price rate per time step driven
- C_{m1} : cost of maintaining one vehicle per time step driven
- C_r : cost of relocating a vehicle per time step driven
- δ_{ij}^{t} : travel time, in time steps, between depots i and j when departure time is t
- C_{m2} : cost of maintaining one parking space per day
- C_ν : cost of the depreciation of one vehicle per day
- M : large number
- $Q_{i,j}^{P}$: demand of vehicles between depots i and j when departure time is t and the price rate is P
- $N_{\max}$: maximum number of depots to create at the N candidate sites
- $Q_{\min}$: minimum share of demand to satisfy

Follow-up study Correia and Antunes (2012) conducted by Jorge et al. (2012). They added the real-time vehicle relocation strategy to the previous study. They proved the application of their model through Lisbon case study.

Nair et al. (2014) developed the model for determining location, size of car sharing station and the fleet size of shared vehicles. Bi-level modeling is deployed in the study. The location and capacity of the station for maximizing revenue from shared vehicle flow is determined by the upper model and the transit flow based on optimal strategy is decided at the lower model. They analyzed several synthetic instances according to the construction cost and budget and found out the trade-offs between operator and user objectives.

Boyaci et al. (2015) studied on a multi-objective MILP(Mixed Integer Linear Programming) model for planning one-way car sharing system taking into account vehicle relocation and electric vehicle charging requirements. To cope with the complexity of the problem, they introduced an aggregate model using the concept of the virtual hub. From the case study for Nice in France, they quantified the trade-off between operator's and user's benefits, and provided insights regarding the efficient planning of one-way electric car sharing systems.

2.2.2. Flow-Capturing Location-Allocation Model(FCLM)

FCLM is the problem of determining optimal location among the candidates existing on the route from the origin and destination to maximize flow. In other words, if the facility on the candidate sites is decided, then the traffic flow on the route is assigned and captured, and FCLM has become the basis for later charging location models.

The first study related to FCLM was conducted by Hodgson (1990) for location selection of convenience stores and ATM. The objective of this model is to maximize the flow using facilities. He solved this NP-hard problem through a 25-node network using the greedy heuristic algorithm. The model formula presented by Hodgson

(1990) is as follows.

$$Max.\ Z = \sum_{q \in Q} f_q y_q$$

subject to,

$$\sum_{k \in N_q} x_k \geq y_q$$

$$\sum_{k \in K} x_k = p$$

$$x_k,\ y_q \in \{0,1\}$$

where,

- q : index of OD pair assigned on the shortest route
- Q : a set of OD pairs
- K : a set of facility candidate locations
- N_q : a set of facility candidate locations on the route q
- f_q : traffic volume assigned on q
- y_q = 1 if f_q is captured, otherwise 0
- x_k = 1 if facility is located on k, otherwise 0
- p : the number of facilities to be determined

Khakbaz (2012) adopted FCLM on determining the location of park-and-ride facilities. The objective function in this model is to maximize the reducing traffic volume, and he used GA to solve the problem. Isfahan in Iran is deployed to the case study, and he analyzed optimal park-and-ride location according to given number of the facility.

Ko et al. (2014) applied FCLM on deciding RFID reader location for monitoring vehicles for Weekly No-Driving Day program in Seoul, South Korea. Base on FCLM proposed by Hodgson (2009), they compared the efficiency of current and proposed RFID reader locations. From the historical data of RFID, they construct the model for the trip pattern, and they found out that detection rate increased from 7.8% to 10% after locating sensors from the developed model.

Lee. (2013) developed UE-based location model of EV considering different battery state-of-charge. Under the statistical assumption of various state-of-charge of the vehicle, he developed the model to find out optimal charging location to minimize travel time cost and penalty due to the failure of EV use. The model structure of his model is bi-level, which charging station is determined in the upper model, and user's route choice is decided in lower model. Unlike previous studies, he used user equilibrium(UE) assign model to mimic user's move more realistically. Simulated annealing algorithm is used to solve the problem.

Mohammad et al. (2017) developed FLCM on the location of refueling station for hydrogen fuel vehicle. In their study, a discrete, robust optimization model considering the refueling demand uncertainty of the hydrogen fuel vehicles market is provided. To this end, delay in charging is reflected through the function of charging time. The objective function is to minimize the total construction cost, the total system travel time, and the refueling delay. They also used bi-level model including UE assign, but they use GA for solving the problem.

The following table shows the summary of literature reviews on the location model for depot.

<Table 2-1> Summary of reviews on location model

Author (year)	Objective	Vehicle assignment	Algorithm	Application network	Remark
Correia. & Antunes. (2012)	Max. profit of operator	Shortest path	Branch & Cut	Real world network (75 nodes)	One-way car sharing
Jorge. Et al. (2012)	Max. profit of operator	Shortest path	Branch & Cut	Real world network (100 nodes)	One-way car sharing
Nair. et al. (2014)	Max. net revenue of user	Shortest path	Branch & Bound	Toy network (24~26 nodes)	One-way car sharing
Boyaci. et al. (2015)	Max. net revenue of user and operator	Shortest path	Branch & Bound	Real world network (100 nodes)	One-way car sharing
Hodgson (1990)	Max. flow covered	Shortest path	Greedy Heuristic	Toy network (25 nodes)	FCLM
Khakbaz (2012)	Max. removed traffic	Shortest path	GA (Meta heuristic)	Real world network (73 nodes)	FCLM
Lee. (2013)	Min. charging failure and congestion cost	Minimum travel time (UE)	SA (Meta heuristic)	Sioux Falls & real world network (73 nodes)	FCLM
Ko et al. (2014)	Max. flow covered	Shortest path	Stepwise location decision	Real world network (424 nodes)	FCLM
Mohammad et al.(2017)	Min. refuel delay time and N/W cost	Minimum travel time (UE)	GA (Meta heuristic)	Sioux Falls network (24 nodes)	FCLM

2.3. Genetic Algorithm

2.3.1. Summary of GA

GA is a parallel and global algorithm developed by Holland (1975). It is based on Darwin's principle of natural evolution, survival of fittest and natural selection. It is a meta-heuristic technique that provides an approximate solution of a complex problem at a relatively reasonable time through the probabilistic search for solution space. (Na. 2008)

Living organisms have a higher probability of survival and individuals evolve in a better way through selection, crossover and mutation processes whereas individuals of unsuitable traits are gradually removed through the process of evolution. This evolutionary process is the main content of GA that will form the most suitable individuals for a given environment as the generations are repeated. Based on these concepts, the main terminologies of the genetic algorithm is as follows.

<Table 2-2> Main terminology in GA

Terminology	Explanation
Individual	One small group characterized by chromosomes
Population	The number of chromosomes in the generation
Gene	The basic components that define the characteristic of an object
Chromosome	The group of multiple genes and it usually expressed by string
Fitness	A value that evaluates the ratio of the fit of each individual gene to the environment

Genetic algorithms are a global and stochastic optimization method different from other algorithms. Classic algorithms are constructed with sufficient knowledge of the controller and mathematical computation of the system. Such a designed system can be local in a given environment and can be seriously influenced by the designer's experience. However, since GA is likely to find globally optimal solutions and there are few mathematical constraints on objective values, it can be applied to many fields. The difference of the GA against the existing optimization algorithm is as follows.

- GA does not use the parameters themselves, but rather code sets of parameters.
- GA uses a set of solutions, which is called population, rather than a single string in the search space.
- GA uses stochastic rules rather than deterministic rules.
- GA does not require information on optimization functions such as differentiability and continuity but uses only fitness values.

The major operations of the GA algorithm are as follows.

1) Selection

The selection is an operation for selecting two parent chromosomes used for crossover. There are various selection operations, but the common principle is that the probability of choosing a good chromosome should be high. The selection probability of a chromosome is controlled by the difference in fitness index between superior and inferior chromosomes. This difference is called selection pressure. The higher the selection pressure, the faster convergence is, but the higher the likelihood of premature convergence, and vice versa. Typical selection techniques include the following.

○ Roulette wheel selection

Roulette wheel selection is a method that enables probabilistic random search by assigning high selection probabilities to individuals having a good fitness index and giving a small selection probability to bad individuals as in a roulette game. The procedure of roulette wheel selection is as follows.

step 1) Calculating fitness index ($fit(s_i)$) of each chromosome (s_i)

step 2) Calculating selection probability of each chromosome (p_i) after calculation of total fitness index (F) of population

$$F = \sum_{i=1}^{pop-size} fit(s_i), \quad p_i = \frac{fit(s_i)}{F}$$

step 3) Calculating the cumulative probability of each chromosome (s_i)

$$q_i = \sum_{j=1}^{i} p_j$$

step 4) Generating chromosomes for a new population through rotating roulette by population size($pop-size$)

(By generating random number (r) in the range [0,1], the first chromosome (u_1) is selected in case of $r \le q_i$, otherwise ith chromosome (s_i) is selected in case of ($q_{i-1} < r \le q_i$)

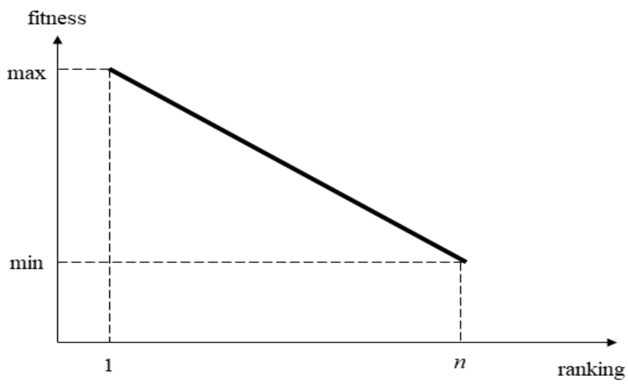
○ Tournament selection

A random number(r) in the range [0,1) is generated for arbitrary two chromosomes. If this value is better than the comparison parameter(t), a solution with good quality is selected and vice versa. The value less than 0.5 is unreasonable, and the higher the value, the higher the selection pressure. 2^k chromosomes are selected and these are compared with fit in the tournament format, and finally, one solution is selected.

○ Ranking based selection

Ranking based selection is a method using the linear function of the rank of fitness index. After calculation of all fitness index for all chromosomes in a generation and sorting by fitness index, the selection probability of them is decided based on the linear function of rank. The fitness of the chromosome with rank i of the n chromosomes can be calculated by the following equation and the selection pressure can be adjusted by changing the difference between max and min values.

$$f_i = \max + (i-1) \times (\min - \max)/(n-1)$$

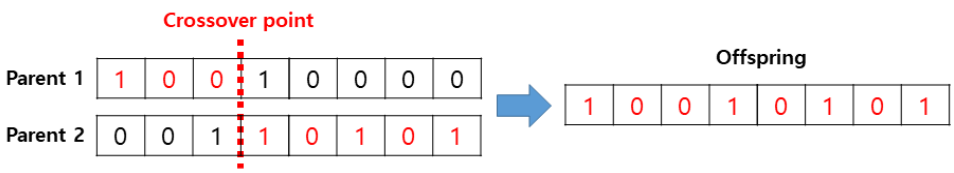


[Figure 2-3] Fitness function of ranking based selection

2) Crossover

Through the selection process, the solution evolves to the highest fitness, but it is difficult to create a new entity. Therefore, the crossover process is performed to generate offspring chromosomes having different genes by gene exchange.

For example, if parent chromosomes 1 and 2 selected by the selection process, and random numbers k, crossover point, smaller than the length of the string is selected, then the parts of the parent chromosomes are exchanged each other based on crossover point(k). The example of crossover when k=3 is shown in the figure below.

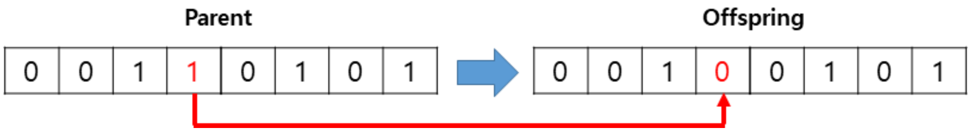


[Figure 2-4] Concept of simple crossover

Types of crossover include a simple crossover with one crossover point, multi-point crossover with two or more crossover points, and uniform crossover that each gene can be independently exchanged. Crossover process spreads the current population globally by combining chromosomes with high fitness index, and it is not a process in other optimization algorithms.

3) Mutation

Selection and crossover are the procedures for creating a new chromosome through searching and combining individual chromosome in the population using the information held by them. On the other hand, mutation is the process to provide new information that does not exist in the present population, and it helps not to focus optimal local value. In the mutation process, a random number in the range [0,1] is generated for each gene in the chromosome, and the bit number is changed if the random value of the corresponding bit is larger or smaller than the given mutation rate. If the probability of mutation is too high, the probability of searching solution in a bad direction becomes large. Therefore, a proper mutation probability should be designed. The figure below shows an example of a mutation, and the fourth bit changes from 0 to 1.



[Figure 2-5] Concept of mutation

4) Fitness and Termination condition

The fitness is the basis of the evaluation of each object to be optimized. In general, the value of the objective function is used as the fitness value in the optimization problem.

When the newly formed solutions(chromosomes) satisfy the appropriate convergence range or reaches the maximum number of generations initially set, the calculation is terminated. In general, the convergence condition is determined to be converged when the chromosomes with the best fit no longer improve, or when the overall fitness does not evolve, or when the value of $(f_{\max} - f_{avg})$ is close to zero (Srinivas et al., 1994).

5) Design parameter

In searching solution by GA, it is important to appropriately combine exploration of unknown areas with the effective exploitation of acquired information. The effective exploitation of the acquired information is similar to the existing hill-climbing method, and the more the search for the unknown area is emphasized, the more the random search becomes. GA is an algorithm that can control both of these conditions together. Important parameters for controlling this are the population size (M), the crossover rate (P_c), and the mutation rate (P_m).

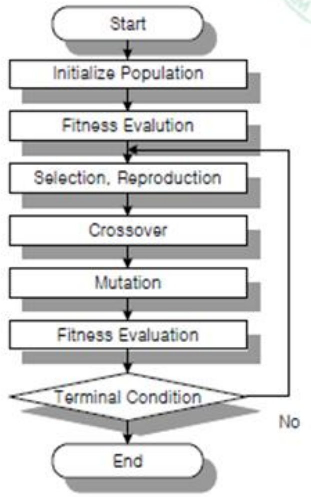
In general, a large P_c and P_m improve the searching ability of the algorithm, which is advantageous in finding a search space with high fitness at the initial stage of evolution. However, it can act as a factor to lower the convergence speed after finding a somewhat good solution by lowering the searchability. Conversely, small P_c and P_m show the opposite characteristics.

Meanwhile, if the size of the population is small, the time required to calculate the fitness can be saved, but the risk of convergence before the optimal solution is obtained due to the rapid loss of diversity among individuals. On the other hand, if the population size is large, the probability of reaching the optimal solution is high, but it requires a lot of computational storage capacity and time.

Therefore, the method of determining the optimal size of the population depends on the type of the problem and the value of the other control parameters.

Based on the GA structure described above, the algorithm pseudo code and the general processing sequence are as follows.

```
Produce Initial n chromosome ;
Repeat {
    for i = 1 to k {
        select parent chromosome(p1, p2) ;
        offspring_i = crossover(p1, p2) ;
        offspring_i = mutation(offspring_i) ;
        }
    Replace offspring_i, … ,offspring_k with k-
    chromosome in the population
    Fitness evaluation
} until satisfying terminal condition
Return best chromosome in the population ;
```



[Figure 2-6] Pseudo code and general flow of GA

2.3.2. Studies on location model deploying GA

Location problem is known as the NP-hard problem because the number of possible solutions increases exponentially with the number of candidate sites or network size. Therefore several meta-heuristic algorithms are used to solve the problem within a reasonable time in various study domains, and GA is one of them. Previous studies related to the GA-based location model are presented along with the main design parameters in GA as follows.

<Table 2-3> Summary of location model studies using GA

Author (year)	Type of problem	Decision variable	Objective function	Population size	Mutation rate	Crossover rate
Ho et al. (2005)	Multiple depot vehicle routing	Vehicle route	Min. total delivery time	25	0.2	0.4
Topcuoglu et al. (2005)	Uncapacitated hub location problem	Hub station	Min. total cost	200	0.4	0.7
Lim & Cuby (2010)	Alternative fuel station problem	Fuel station	Max. total flow	200	0.1~0.2	-
Khakbaz et al. (2013)	Park and ride facility location problem	Facility location	Max. total flow	Case by case	0.5	0.5
Owais et al. (2015)	Transit route network design problem	Bus stop	Min. user and operator cost	400	0.15	0.75
Amir et al. (2016)	Dynamic hub location problem	Covering radius	Min. total cost	200	0.1	0.85

2.4. Review Results and Originality of the Study

The implications through literature reviews can be summarized as follows. First of all, some previous studies using AV in the field of shared mobility, have been conducted on the assumption that the services are driven by the private sector rather than the public sector. Therefore, they use flow maximization or profit maximization as an objective function to determine the location of depots, and social costs (e.g. network congestion cost) is not sufficiently considered. However, it can be seen that on-demand transportation services using AV can generate sufficient demand even in comparison with current public transport, from several SAV-related studies. In addition to this, DRAV in the public sector can also be competitive with producing social benefits such as improved travel convenience for vulnerable road users, energy saving, and emission gas reduction. Public institutions, responsible for road management, need to consider the social benefits from implementing DRAV system rather than focusing on making a profit. Therefore, it is necessary to conduct a comprehensive study considering both social and actual costs to establish a DRAV depot installation for the public interests.

Second, the network congestion cost due to empty vehicle travel has not been taken into consideration in the previous studies, although many studies pointed out that the road congestion due to empty vehicle travel should be solved for successful AV diffusions. Road congestion, caused by the empty vehicle travel, may accompany huge congestion costs with the increased use of DRAV especially in congested areas such as urban roads. Therefore, road congestion due to empty vehicle travel should be considered for the model development.

Third, the realistic description of the movement behavior of the vehicle is insufficient. Most studies related to the location of depot concerning shared mobility such as one-way car sharing utilized the shortest path based traffic assignment. However, it is necessary to apply the route choice model based on the minimum travel time to represent more realistic travel behavior. Additionally, considering the social costs from empty vehicle travel in the DRAV depot decision process, it is necessary to construct a more realistic model through route choice based on the minimum travel time such as UE.

The improvement direction and the originality of this study based on the implications above are as follows.

First, not only system introduction cost from operator's view but also social cost from user's viewpoint are considered when constructing a model for determining location, quantity, and capacity of DRAV depot. The social cost of the user is reflected as the travel time cost (TTC) of the user travel after the implementations of the DRAV system. In this process, additional network congestion due to the empty AV travel, which is not considered in the previous studies, is considered. Operator costs contain the vehicle purchasing, depot construction, and land purchasing costs for public institutions' DRAV system implementations.

Second, a bi-level model iteratively represents changes in user behavior according to the determined depot locations. The upper model determines the location, quantity, and capacity of the depot. Lower model conducts a modal split and a traffic assignment considering the empty AV travel which depends on the upper model results. In the lower model, modal split and traffic assignment, which represents the updated link travel time due to empty AV travel time from determined depot locations, are iteratively conducted until the network total travel time is converged. UE traffic assignment model is applied for auto and AV, and optimal strategy based traffic assignment is applied for public transportation to illustrate more realistic user route choice based on travel time rather than the shortest path.

Third, this study develops a meta-heuristic algorithm to find out an optimal solution of NP-hard problems within a reasonable time. As the quantity of depot is not given in the problem of this study, the pattern of solution varies greatly depending on the quantity of depot. Therefore, this study developed an algorithm that takes into consideration the characteristics of the problem where various local optima exist.

Finally, various policy implications are derived from several scenario analyses based on the change of transportation environment. To enhance the applicability of the model in this study, various scenarios regarding OD, vehicle passenger and the fare can be considered.

3. Model Formulation

3.1. Problem Definition

3.1.1. Terminology

Before constructing the model, the terms used in this study are summarized as follows.

<Table 3-1> Terminologies

Terminology	Explanation
DRAV	• New type of demand responsive self-driving para-transit operating between user's OD, and it can be substituted the current transportation modes such as auto and bus
Depot	• The building which DRAV wait for the service, and its capacity is determined by DRAV fleet size under certain service level
Depot Capacity	• The size of depot and it also means that the number of DRAV should be prepared at each depot
Empty Vehicle Travel	• DRAV traffic traveled by empty vehicle between depot and user's origin(or destination) zone for DRAV service
Pre-implementation/ Post-implementation	• Pre-implementation : Situation before DRAV system is implemented • Post-implementation : Situation after DRAV system is implemented
Travel Time Cost (TTC)	• Sum of travel time cost by modes in the network due to the implementation of DRAV system • Travel time of each mode is determined by VDF function
Operation Cost (OC)	• Sum of cost concerning vehicle and depot after implementation of DRAV system
Total Cost (TC)	• Sum of travel time cost and operation cost

3.1.2. Assumptions

This study is based on the assumption of the introduction of DRAV system which is expected to be introduced in the near future. The assumptions of this study are as follows.

1) General situation

- Temporal situation is after 2030 when self-driving AV is commercialized
- Only auto, bus, and DRAV is considered as traffic modes
- Land cost of all candidates for depot location is same
- After the introduction of DRAV system, the existing auto users do not sell their vehicles, and operating frequency of bus is unchanged

2) Modal split

- Vehicle occupants of DRAV is 2 under the assumption of activation of ride sharing
- Fare of DRAV between user's OD zone is determined based on the current one-way car sharing price scheme, and it is additionally split by the number of in-vehicle passengers
- Mode specific constant of taxi in the manual is applied for that of DRAV

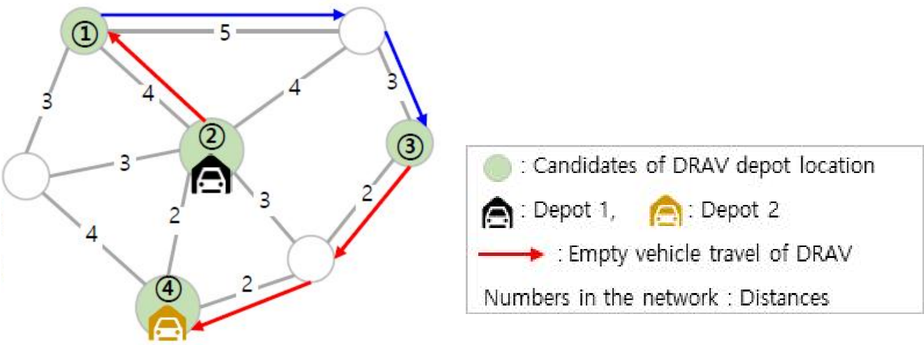
3) DRAV Service

- DRAV is based on-demand service with flexible operating route and timetable

- DRAV travels on the route with the minimum travel time, and it provides one-way service, not round trip service
- The vehicle of depot closest to the user's origin is assigned to the service
- Considering operational efficiency and construction constraints, the fleet size of each depot should be between 30 and 150, and the unit of fleet size is 10.
- Each depot should have a vehicle that meets peak hour DRAV demand

3.1.3. Problem situation

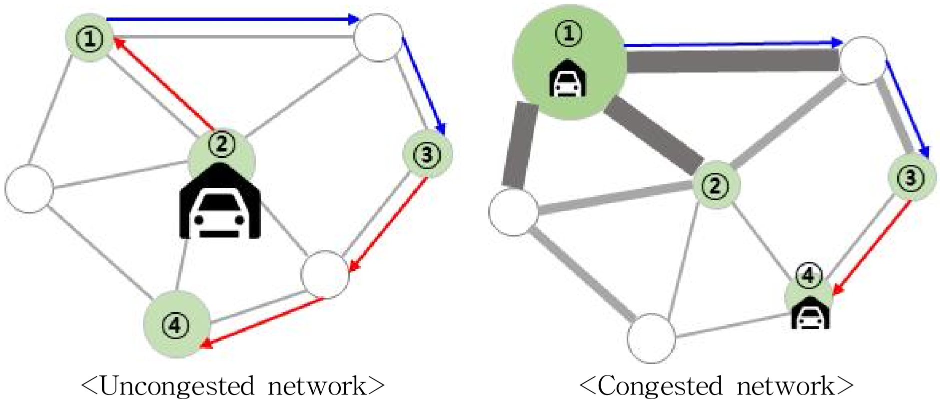
The situation of empty vehicle travel with the example of DRAV demand traveling from zone ① to zone ③ is presented in the figure below. Assuming that there are two DRAV depots in the network (1: Black, 2: Yellow), DRAV demand in zone ① will use depot 1 (Black), which is nearest one to origin zone (zone ①). Therefore, empty vehicle travel occurs from depot 1 to zone ① as expressed red arrow in the figure. Likewise, empty vehicle travel occurs between zone ③ and depot 2, where is the shortest route between the destination zone and its closest depot. In the present study, empty vehicle travel generated differently according to the location of the DRAV depot is reflected as the additional congestion cost in the objective function.



[Figure 3-1] Concept of empty vehicle travel of DRAV

The main motivation of this study is that empty vehicle travel can differently affect network congestion according to the congestion level. Therefore, the increase of DRAV demand and existence of chronically congested sections can affect the determination of depot location, quantity and its capacity. For example, in the following figure, a large-scale depot that satisfies a certain level of service level for all DRAV demand in the network can be installed in the node ②, which is network hub node, in a non-congested situation. However, if the same amount of DRAV demand is concentrated in the zone ① or if the traffic on surrounding roads is congested in the zone ①, it can be better to install the depots separately in the zone ① and zone ④ by reducing social cost.

This is because there is a trade-off between the cost of network congestion due to empty vehicle travel of DRAV and the cost of introducing DRAV system. In other words, if a lot of depots are installed in the network, the congestion cost due to the empty vehicle travel is lowered, but the cost of installing the depot is further increased. Conversely, if there are few depots installed, depot construction costs will be low, but network congestion costs will increase. In particular, the network congestion cost can be increased exponentially as travel time increase, so the location, quantity, and capacity of different depots can be determined differently according to traffic environments although the amount of OD trip is same.



[Figure 3-2] Concept of change in depot locations under same total DRAV trips

3.2. Notations and Framework

3.2.1. Notations

The notations used in the present model are shown below.

<u>Sets</u>

- N: node set
- R: route set $(r \in R)$
- I: origin set $(i \in I, I \subset N)$

- J: destination set $(j \in J, J \subset N)$
- K: depot candidates set $(k \in K, K \subset N)$
- M: mode set $(m = a : auto, b : bus, s : DRAV)$

<u>Decision Variables</u>

- Z_k : 1 if depot is located on candidate k, otherwise 0
- S_n : the number of depots in the network
- $S_{cap,k}$: capacity of depot k (DRAV fleet size in depot k)
- $\widehat{Q^{ki}}$: empty vehicle travel of DRAV from depot k to node i
- $\widehat{Q^{jk}}$: empty vehicle travel of DRAV from node j to depot k
- $x_{a,m}$: traffic volume on link a by mode m

<u>Other Variables</u>

- Q^{ij} : total demand from node i to j
- Q^{ij}_m : total demand of mode m from node i to j
- $f^{ij}_{r,m}$: traffic volume of mode m on route r from node i to j
- T^{ij}_m : total travel time of mode m from node i to j
- C^{ij}_m : cost of mode m from node i to j
- $P(m)$: probability of selection of mode m
- U^{ij}_m : utility of mode between origin and destination
- $(T_{TIME})^{ij}_m$: total travel time of mode k between i and j
- $(T_{COST})^{ij}_m$: total travel cost of mode k between i and j
- t_a : travel time on link a ($t_{a,m}$: travel time of mode m on link a)

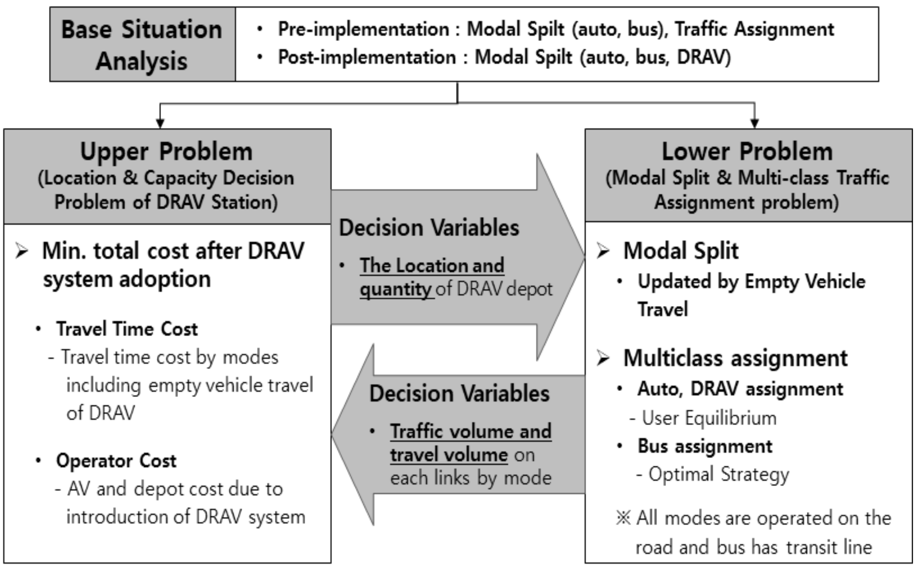
- δ_{ar}^{ij} : 1 if link a is on route r from node i to j, otherwise 0
- f_a: frequency of link a
- w_n: waiting time on node n
- A_n^+: link set outbound node n
- A_n^-: link set inbound node n
- g_n: transit volume from node n

<u>Parameters</u>

- τ_m: value of time of mode m
- B : very large value (dummy value)
- S_{cap}^* : maximum capacity of depot
- S_{cap}^- : minimum capacity of depot
- $Occp_s$: vehicle occupant of each depot s
- D_m : mode specific constant
- α_1, α_2 : coefficients of travel time and cost in utility function

3.2.2. Model framework

This study minimizes total cost, which is changed according to the location of depot due to the introduction of DRAV system. The total cost is calculated as the difference between the cost of pre-implementation and post-implementation. The cost of pre-implementation is computed through base situation analysis regardless of the depot, but the cost of post-implementation is calculated based on the location, quantities, and capacity of depots. Besides, the cost of post-implementation is affected by the road user's choice of mode and route, which is depended on the depot location. Therefore, it should be able to reflect the changing behavior of the user depending on the location of various depots iteratively. To do this, bi-level model is deployed in this study. In the upper model, the location, quantity, and capacity of the DRAV depot are determined, and the lower model determines the user's traffic volume and link travel time by modes according to the depot location determined in the upper model. Traffic volume of each mode and link travel time in the lower model is determined based on the modal split and multi-class transit assignment model. The result of the lower model is again used to calculate the objective value in the upper model. The model framework that shows this is as follows.



[Figure 3-3] Model framework

3.3. Base situation analysis

The base situation analysis of this study calculates the values that are determined regardless of the location of the depot. First, it includes the process of calculating TTC of pre-implementation of DRAV. This process consists of a modal split process of calculating the OD trips by each mode through predetermined total OD volume and parameters for each mode and a traffic assignment process of calculating the OD trips and the travel time of each link by modes. Last procedure is to decide OD trips by modes after DRAV system is introduced modal split. Since modal split in the base situation does not consider empty vehicle travel, it is calculated regardless of depot location.

3.3.1. Modal split

In the present study multinomial logit (MNL), which is based on the utility of travelers, is used for mode choice of users. In MNL, the probability that user will choose a particular transport mode can be expressed as follows.

$$P(m) = \frac{\exp(U_m)}{\sum_{m}^{M} \exp(U_m)}$$

The utility is calculated based on the travel time, cost, and mode-specific constant and general form of the utility function is as follows.

$$U_m^{ij} = \alpha_1 (T_{TIME})_m^{ij} + \alpha_2 (T_{COST})_m^{ij} + D_m$$

In calculating the utility, the travel time means the total travel time by modes, and not only vehicle travel time, but also waiting time, access/egress time, transfer time is included in case of transit. Regarding travel costs, the cost of the auto means the total operating cost including oil, insurance, depreciation. In case of the bus, the fare of the shortest route between origin and destination is adopted for travel cost. Based on the utility function in the MNL, OD trips by modes is calculated by the following equation.

$$Q_b^{ij} = \frac{Q^{ij}}{(1 + \exp(\alpha_1 (T_b^{ij} - T_a^{ij}) + \alpha_2 (C_b^{ij} - C_a^{ij}) + D_b)}$$

$$Q_s^{ij} = \frac{Q^{ij}}{(1 + \exp(\alpha_1 (T_s^{ij} - T_a^{ij}) + \alpha_2 (C_s^{ij} - C_a^{ij}) + D_s)}$$

$$Q_a^{ij} = Q^{ij} - Q_b^{ij} - Q_s^{ij}$$

The parameters for the travel time and the travel cost for each mode applied in this study are the values provided by the manual of the preliminary feasibility study in Korea as shown the table below. By the model assumption, the parameter of the taxi is applied to DRAV because taxi has the most similar characteristics to DRAV.

<Table 3-2> Parameters by modes in utility function

Mode	Travel time	Travel cost	Constant
Auto	-0.05069	-0.00033	-
Bus			-0.65488
Taxi			-1.05534

3.3.2. Multi-class traffic assignment

The choice of the route of the user by modes is determined by the model which chooses the route minimizing travel time of the user. The modes considered in this study are auto, bus, and DRAV. Among them, the bus has different operating characteristics from auto and DRAV because it is a public transportation system operated according to fixed route and timetable. To account for this characteristic, different traffic assignment models are applied to each of them.

1) Assignment of auto

For assignment of auto, user Equilibrium (UE) model that selects a path that minimizes the user's travel time. This is based on the Wardrop's 1st principle (1952) that the user chooses the route that minimizes his travel time. Beckmann et al. (1956) developed a mathematical model for estimating the amount of traffic in this equilibrium state, as follows

.

$$\min \sum_a \int_0^{x_a} t_a(w)dw$$

$$\text{s.t. } x_a = \sum_i \sum_j \sum_r f_r^{ij} \cdot \delta_{ar}^{ij}, \ \forall a$$

$$\sum_{r \in R} f_r^{ij} = Q^{ij}$$

$$f_r^{ij} \geq 0$$

If the travel cost function of each link is convex, it proved that the objective function of the model is always convex and have a unique solution. Also, this unique solution has proven to be equivalent to Wardrop's first principle, which can be used as a passenger car assignment. The BPR function, which is a typical link travel cost function, used for auto assignment in this study, and it is defined as follows.

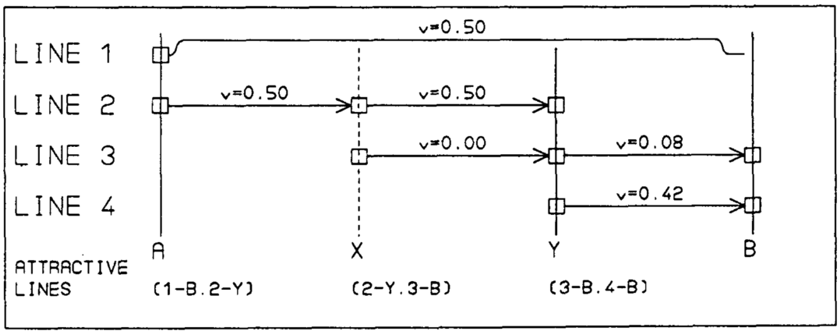
$$t_a(x_a) = \frac{l_a}{\overline{v_a}} \cdot \left[1 + \alpha\left(\frac{x_a}{c_a}\right)^{\beta}\right] \qquad \forall a \in A_r$$

where,

- l_a: length of link a
- $\overline{v_a}$: free flow speed of link a
- α, β: parameters of link travel time function
- x_a: traffic volume of link a
- c_a: capacity of link a

2) Assignment of bus

Bus, one of the representative transit, is operated with fixed line and timetable. Therefore, traffic assignment model which can be considered the characteristics of transit such as waiting time and frequency should be adopted in the model. Therefore optimal strategy, which is developed by Spiess and Florian (1989), is adopted for assignment the of bus in the present model. In the model, it is assumed that passengers can get the only information of which line is served next during waiting at the depot. All trips are generated by the strategy minimizing total passenger's travel time which includes waiting time.



[Figure 3-4] Illustration of optimal strategy

The process of optimal strategy is shown below.

Step 0) Set origin node to NODE

Step 1) Board vehicle which arrives first among the vehicles of the set of attractive lines at NODE

Step 2) Alight at predetermined node according to the optimal strategy

Step 3) If not yet at destination, set current node to NODE move to Step 1); otherwise the trip is completed

The optimal strategy explained above can be formulated as shown below.

$$\min \sum_a x_{a,b} t_{a,b} + \sum_n w_n$$

$$\text{s.t.} \sum_{a \in A_n^+} x_{a,b} - \sum_{a \in A_n^-} x_{a,b} = g_n \quad n \in N$$

$$x_{a,b} \leq f_a w_n, \ a \in A_n^+, \quad n \in N$$

$$x_{a,b} \geq 0, \ a \in A$$

3.4. Upper model

3.4.1. Objective function

The objective function of the upper model minimizes the total cost including the travel time cost and the operation cost that may occur depending on the location, quantity and the capacity of the depot. To unify the units, TTC uses the value of time to convert the annual social cost into monetary cost, and the operating cost uses the yearly cost considering the depreciation.

$$\text{Objective} = \min \sum_{m \in M} \mathit{Travel\ Time\ Cost} + \mathit{Operator\ Cost}$$

<Table 3-3> Value of time by modes in manual

구분	Auto		Bus		DRAV	
	Work	Non-work	Work	Non-work	Work	Non-work
Ratio of trip purpose(%)	8.42	91.58	1.14	98.86	4.78	95.22
Vehicle occupant (peo.)	0.15	1.13	1.11	9.37	0.10	1.90
Value of Time(won/veh.)	14,838		60,987		21,370	

1) Travel Time Cost (TTC)

The travel time cost in this study is defined as the social cost of the travel time for the user of auto, bus, and DRAV due to the introduction of DRAV system. This can be calculated by the difference in the sum of TTC by modes before and after the introduction of the system. TTC for each mode is computed by multiplying the traffic volume, the travel time, and the value of time for each mode as shown below.

$$\sum_{m \in M} TTC = \sum_{m \in M} TTC_{post} - \sum_{m \in M} TTC_{pre}$$

$$TTC = TTC_{auto} + TTC_{bus} + TTC_{DRAV} = \sum_{a,m} (\tau_m \bullet t_a(x_a) \bullet x_a)$$

In this study, the changes of TTC by modes after DRAV system introduction are as follows. In the case of auto and bus, TTC is a negative (-) value because of the decrease in traffic volume due to the modal shift to DRAV. On the other hand, TTC of DRAV have

(+) value by the amount of traffic volume shifted from auto and bus after implementation of the system. Besides, there is a trade-off in TTC in post-implementation due to vehicle occupant of DRAV, which is two by the assumption. The number of vehicles on the road can be reduced as the number of volumes shifted from auto increases, but there would be additional empty vehicle travel of DRAV on the road by the amount of shifted volume.

2) Operation cost

Operation costs consist of fixed costs and operating cost associated with vehicle and depot installations after the system implementation.

The vehicle cost of DRAV composes the sum of the purchase cost of the general car in the manual and the cost of the autonomous driving function. The cost of the autonomous driving function is applied from approximate average costs suggested by the related studies[1]. The depot related costs are referred to the method of estimating the parking building cost in the manual. Depreciation cost considering the period of duration is used for the fixed cost of vehicle and depot.

The details of the cost items are as follows.

$$\sum OC = \sum OC_{DRAV} + \sum OC_{Depot}$$

1) Autonomous vehicle implementation predictions(VTPI, 2007), The road to autonomous vehicle(BCG, 2015), Google AV price

<Table 3-4> Configuration of operation cost of DRAV system

Category		Contents	Reference
Vehicle (DARV)	Fixed Cost	AV Purchasing cost	MPFS[2],
	Operating Cost	Maintenance, Depreciation, Oil	
Depot	Fixed Cost	Construction cost	MIATF[3]
		Other fixed cost including land cost	
	Operating Cost	Personal expense, Overhead, Maintenance	

- Purchasing cost of DRAV : 7.5(million won/veh/year)
  - vehicle purchasing cost : 21(million won/veh)
  - self-driving function cost : 39(million won/veh)
  - period of duration : 8 years
- Operating cost of DRAV : auto operating cost by manual(MPFS), which is calculated by auto speed on individual link.
- Construction cost of depot : 33.9(million won/depot/year) + 0.87(million won/veh/year)
  - modified cost of building type parking lot in manual(MIATF)
- Other fixed costs for depot including land cost : 80(million won/depot/year)
  - cost of parking building with 20 vehicles per level.
  - period of duration : 20 years
- Operating cost of depot : 202(million won/depot) + 1.3(million won/veh)
  - modified cost of building type parking lot in manual(MIATF)

2) manual of the preliminary feasibility study for project of roadway and railway (Korea Development Institute. 2008.12)

3) Manual of investment appraisal for transportation facility. (Ministry of Land, Infrastructure and Transport, 2017.06)

3.4.2. Constraints

The constraints of the upper model are the following conditions to be considered in determining DRAV depot location.

1) Trip generation constraint of empty vehicle travel

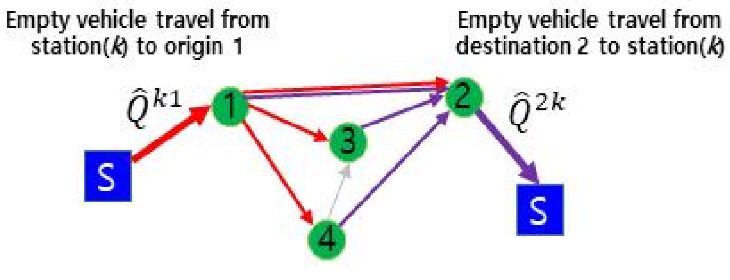
The first constraint is that the empty vehicle travel of DRAV only occurs in the installed depot. It can be seen from the big value constraints below that the even a lot of empty vehicle travel can occur only at the installed depot among candidates.

$$\widehat{Q^{ki}} \le Z_k \cdot B, \quad \widehat{Q^{jk}} \le Z_k \cdot B, \quad \forall i \in I,\ \forall j \in J,\ \forall k \in K$$

2) Traffic volume conservation of empty vehicle traveled

The second constraint is traffic volume conservation constraint that the volume of empty vehicle travel at a certain depot is the same as the sum of DRAV demand using that depot. For example of the figure below, the volume of empty vehicle travel generated from a specific depot to a specific zone 1 ($\hat{Q}^{k1}$) is equal to the sum of the demand for DRAV use from the origin 1 to all the destinations. This also applies to the volume of empty vehicle travel ($\hat{Q}^{2k}$) generated after using the DRAV service.

$$\widehat{Q^{ki}} = \sum_{j \in J} Q_s^{ij}, \quad \forall i \in I,\ \forall k \in K \qquad \widehat{Q^{jk}} = \sum_{i \in I} Q_s^{ij}, \quad \forall j \in J,\ \forall k \in K$$



[Figure 3-5] Concept of traffic conservation of empty vehicle travel

3) Depot capacity constraint

The following constraints are constraints on depot capacity. This is the constraint not only on the maximum depot size considering land utilization and building condition but also on the minimum depot size considering the efficiency of the operation.

$$S_{cap}^{-} \leq S_{cap,k} \leq S_{cap}^{*}, \qquad \forall k \in K$$

4) Service level constraint

The last constraint is about DRAV system service level, which determines how many AV should be prepared in the depot. According to the assumption of this study, each depot should have a vehicle that meets at least the peak hour of DRAV demand using each depot. This means that the size of each depot has minimum capacity constraint concerning service level. This can be expressed as follows.

$$S_{cap,k}^{*} \geq \sum_{i \in I} \sum_{j \in J} \frac{Q_s^{ij_{peak}} \cdot \hat{T}_s^{ij}}{Occp_s}, \qquad \forall i \in I,\ \forall k \in K$$

3.5. Lower model

The lower model of this study is a model describing the passengers' behaviors by modes under a given depot location and capacity conditions. Since the purpose of this study is to determine the depot location that minimizes the total cost reflecting the congestion cost due to empty vehicle travel, modal split and traffic assignment are conducted to reflect the purpose in the lower model.

Just the same in base situation analysis, the MNL-based modal split is carried out for auto, bus, and DRAV. Similarly, UE is also adopted for traffic assignment of auto, and the bus applies the optimal strategy traffic assignment. Since DRAV provides on-demand service that does not operate according to fixed routes and timetable, it carries out the same UE assignment as auto. Here, the constraints in UE model is modified to reflect the volume of empty vehicle travel of DRAV determined by the location of the depot in the upper model as shown below formula.

$$\min \sum_a \int_0^{x_a} t_a(w)dw$$

$$\text{s.t. } x_a = \sum_k \sum_i \sum_r f_r^{ki} \cdot \delta_{ar}^{ki} + \sum_i \sum_j \sum_r f_r^{ij} \cdot \delta_{ar}^{ij} + \sum_j \sum_k \sum_r f_r^{jk} \cdot \delta_{ar}^{jk},\ \forall a$$

$$\sum_{r \in R} \sum_{m \in M} f_{r,m}^{ki} = Q^{ki} + \hat{Q}^{ki}, \quad \sum_{r \in R} \sum_{m \in M} f_{r,m}^{ij} = Q^{ij}, \quad \sum_{r \in R} \sum_{m \in M} f_{r,m}^{jk} = Q^{jk} + \hat{Q}^{jk}$$

$$f_{r,m}^{ki}, f_{r,m}^{ij}, f_{r,m}^{jk} \geq 0$$

where,

- $t_a(w)$: travel time on link a $\left(t_a(w) = t_0 \cdot \left[1 + \alpha \cdot \left(\frac{x_a}{c_a}\right)^{\beta}\right]\right)$

4. Algorithm Development

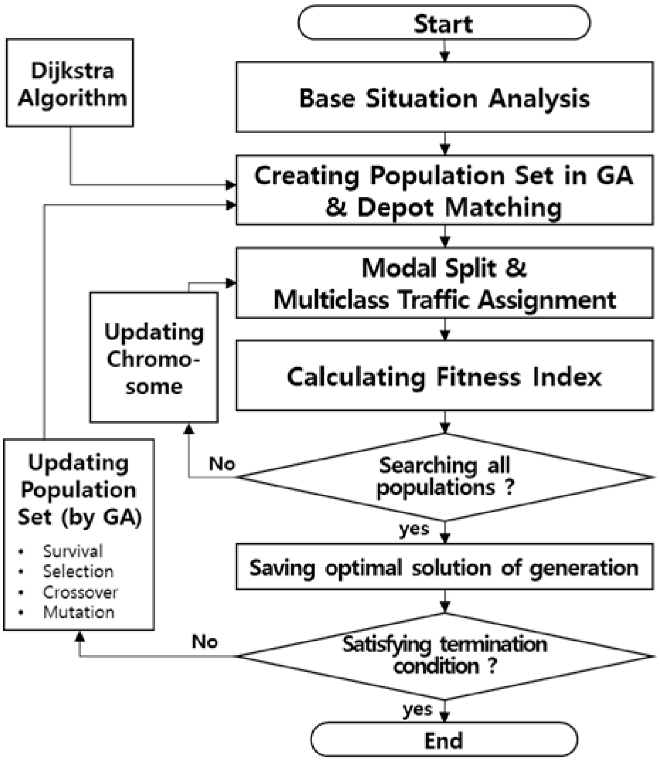
4.1. Outline of Algorithm

4.1.1. Complexity

The problem in the present study is to determine the location, quantity, and capacity of DRAV depot in the upper level model and to decide link travel time and traffic volume by modes in the lower level model. This is categorized into MINLP (Mixed Integer Non-Linear Programming), and it is a form that solves the problems of set covering and the p-median problem at the same time. The complexity of the problem is NP-hard because the range of feasible solution is C^n(C: the number of possible depot capacity expressed by a discrete value, n: the number of candidates of depot). Therefore the problem in the present study is hard to solve in polynomial time based on analytic approach as the size of the network grows. To overcome this difficulty, GA which is a representative meta-heuristic approach is considered in this study. Since the pattern of solution varies greatly depending on the quantity of depot, several local optima can exist. Therefore, the present study considered this characteristic in the algorithm development.

4.1.2. Structure of algorithm

The algorithm starts with base situation analysis. The calculations regardless of the depot location are conducted such as TTC of pre-implementation and OD trips by modes of post-implementation without considering empty vehicle travel. After base situation analysis, GA is deployed to solve the bi-level problem. As the first procedure of the GA, generation of population set and depot matching by Dijkstra algorithm is conducted. Then, modal split and multi-class traffic assignment considering empty vehicle travel, which is affected by the depot location. After computing travel time and OD trips of the link through modal split and traffic, fitness index (FI) is calculated using the result of base situation analysis and multi-class traffic assignment. Through calculation of FI for all population in the generation, the optimal solution of the generation is evaluated by the termination condition. If the termination condition is not satisfied, then the population set for next generation is updated by GA process, which includes survival, selection, crossover, and mutation. This procedure is repeated until the termination condition is satisfied. The algorithm of this study is the shown in figure below, and details of each algorithm step are described in the next section 4.2.

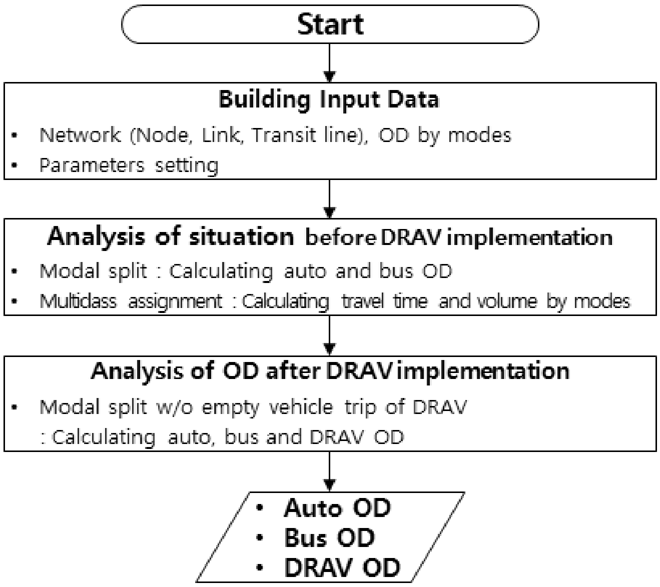


[Figure 4-1] Algorithm flow of the study

4.2. Algorithms for DRAV Depot Decision

4.2.1. Base situation analysis

The base situation analysis starts with building input data such as node, link, transit line and OD trips by modes. The parameters concerning travel time and travel cost for modal split and traffic assignment also predetermined. Then, the calculation of TTC before DRAV system implementation is conducted through the modal split and multi-class assignment concerning auto and bus. Traffic volume and link travel time of each mode are computed as an output of the base situation analysis, and they are used later in calculating FI in GA procedure. The last procedure of base situation analysis is to calculate OD trips of auto, bus, and DRAV after DRAV system is implemented. MNL with predefined parameters by modes is applied to modal choice both before and after implementation of DRAV system.



[Figure 4-2] Algorithm procedure in base situation analysis

To calculate the multi-class traffic assignment problem, UE for auto and DRAV, and optimal strategy for the bus is adopted respectively. The algorithms for those assignment are present as follows.

1) Algorithm for UE

Convex combination method is adopted to solve UE problem in this study. It is useful for determining equilibrium state in the network, and utilizes the linear programming as part of the direction finding step. The method is efficient and well-known algorithm for solving UE problem. The procedure of the method is as shown below.

Step 1) [Initialization] Perform all-or-nothing assignment based on $t_a = t_a(0),\ \forall a$. This yields $\{x_a^1\}$. Set counter $n := 1$.

Step 2) [Update] Set $t_a^n = t_a(x_a^n),\ \forall a$

Step 3) [Direction finding] Perform all-or-nothing assignment based on $\{t_a^n\}$. This yield a set of (auxiliary) flows $\{y_a^n\}$

Step 3) [Line search] Find α_n that solve

$$\min \sum_a \int_0^{x_a^n + \alpha(y_a^n - x_a^n)} t_a(w)\, dw$$

Step 4) [Move] Set $x_a^{n+1} = x_a^n + \alpha_n (y_a^n - x_a^n),\ \forall a$

Step 5) [Convergence test] If a convergence criterion is met, stop (the current solution, $\{x_a^{n+1}\}$, is the set of equilibrium link flows); otherwise, set $n := n+1$ and go to step 1)

2) Algorithm for optimal strategy

The algorithm for optimal strategy is based on the algorithm developed by Spiess and Florian (1989). In a first pass, from the destination node to all origins, the optimal strategy ($\overline{A^*}$) and the expected total travel time (u_i^*) from each node $i \in I$ to the destination node r are computed. In a second pass, from all origins to the destination, the demand is assigned to the network according to the optimal strategy. The detail steps are as shown below.

Part 1. Find optimal strategy

Step 1.1) [Initialization]

$u_i = \infty,\ \ i \in I - \{r\},\ \ u_r = 0;$

$f_i = 0,\ \ i \in I$

$S = A;\ \overline{A} = \varnothing$

Step 1.2) [Get next link]

If $S = \varnothing$, then **stop,**

else find $a = (i,j) \in S$ which satisfies

$$u_j + c_a \le u_{j'} + c_{a'},\ \ a' = (i', j') \in S;$$

$S = S - \{a\}$

Step 1.3) [Update node label]

If $u_i \ge u_j + c_a$, then

$$u_i\ := \frac{f_i u_i + f_a (u_j + c_a)}{f_i + f_a}$$

$$f_i := f_i + f_a,\ \overline{A} := \overline{A} + \{a\};$$

go to step 1.2).

Part 2. Assign demand according to optimal strategy

Step 2.1) [Initialization]

$V_i := g_i,\ \ i \in I;$

Step 2.2) [Loading]

Do for every link $a \in A$, in decreasing order of $(u_j + c_a)$:

if $a \in \overline{A}$ then $v_a := \frac{f_a}{f_i} V_i$, $\quad V_j := V_j + v_a$,

otherwise $v_a := 0$

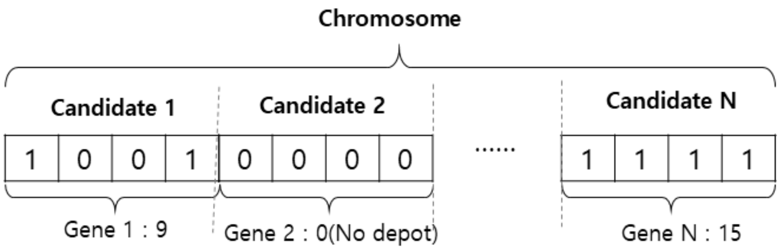
where,

- u_i: the expected travel time to the destination
- f_i: auxiliary variable that contains the combined frequencies of all selected links at node i
- c_a: travel time on link a
- g_i: the demand from node i to the destination node r
- V_i: node volume that corresponds to its frequency

4.2.2. Generation of population set and depot matching

Individual solutions are expressed as chromosomes in GA. Each chromosome represents both the installation of the depot at the node and the capacity of the depot. In this study, the capacity of each depot is assumed to have a capacity of 10 units with the range of 30 and 150 vehicles. This is due to the minimum constraint considering the efficiency of the depot operation and the maximum constraints considering the construction constraints.

The capacity of the depot at each node is represented by a binary 4-bit gene, and each gene has a value between 0 and 15. The actual capacity of the depot is estimated to be ten times the value of each gene, and the maximum capacity per depot is assumed to be 150 in this study. In the figure below, for example, the capacity of candidate node 1 means a depot of size 90 and the candidate node 2 is not installed since the capacity is zero. The individual chromosomes are represented by 4 × N (the number of candidates) bits.



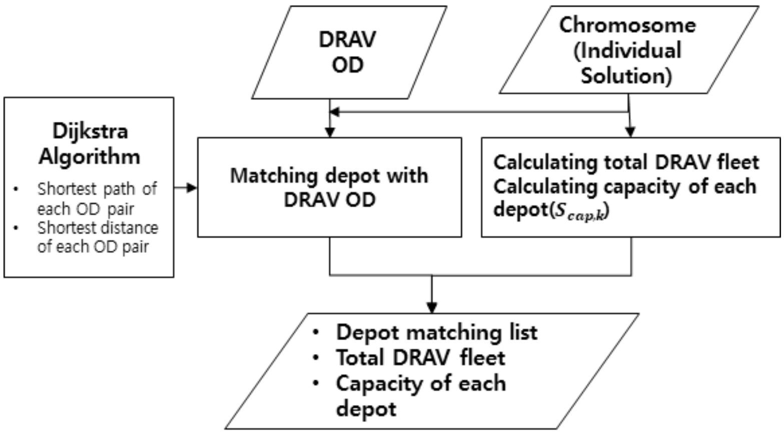
[Figure 4-3] Example of chromosome in the present study

Since this study is a location problem, it is necessary to have the same probability of installing depot is at each node with 50%. To reflect this, the probability that the genes are zero and non-zero in the generation of the initial solution is equal to 50%. And non-zero genes are generated to have the value between 3 and 15 through random number generation. This means that the capacity of the installed depots, which also means the fleet size of the depots, appear at the same probability. The initial set is composed of chromosomes as many as the population set by repeating the above procedure. From the chromosome in the population set, total DRAV fleet and capacity of each depot is determined.

When using the DRAV system, the service AV is selected as the vehicle of the depot closest to the user's origin, and it returns to the nearest depot in the destination zone after the service is completed.

Dijkstra algorithm, which is well-known shortest path algorithm, is applied to match the DRAV users and depot used in DRAV system.

Then, the matching list can be constructed based on DRAV OD which is determined by base situation analysis and individual chromosome. Besides, total fleet size of DRAV and capacity of each depot ($S_{cap,\,k}$) is calculated.



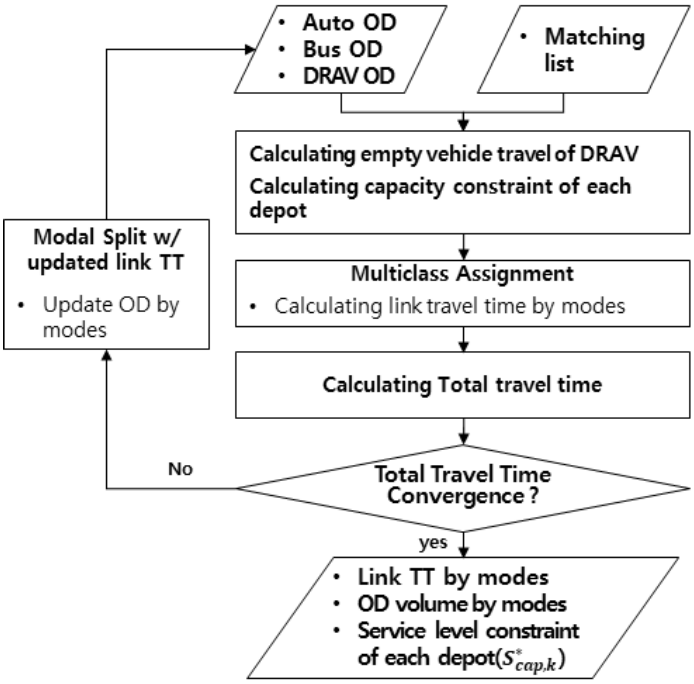
[Figure 4-4] Algorithm procedure in generation of population set and depot matching

4.2.3. Modal split and assignment considering empty vehicle travel

Using the DRAV volumes by mode and matching list, the volume of empty vehicle travel and the service level constraint can be calculated. The service level constraint (S^*_{cap}), which is the minimum fleet size to have at each depot, is determined by the volume of empty vehicle, average service time of each OD pair and vehicle occupants of DRAV. Here, the service time means the total time required for the AV to arrive at the destination depot after the trip service of user's OD, starting from the origin depot (depot→O→D→ depot). By the assumption, each depot should have AVs that can satisfy the DRAV demand for peak one hour.

The reason for reflecting the average service time in determining the service level constraints of the depot is to overcome the limitation of the static model in which the total fleet size is determined only by the demand of DRAV. In other words, for OD pairs with the same demand, relatively few vehicles are required when the total service time is small, and conversely, when the total service time is high, a relatively large number of vehicles are required to maintain a certain level of service. The problem of same fleet size by only OD trips, regardless of the travel distance or the travel time, can be solved by the service level constraint. This is important because it affects the size of the depot. The service level constraint reflecting this can be obtained by the formula in chapter 3.4.2.

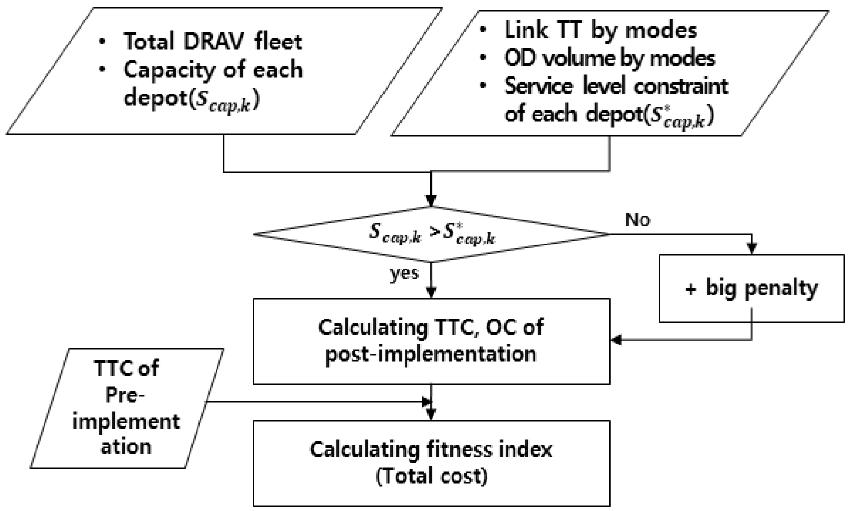
Then, link travel time in the network reflecting the effect of empty vehicle travel can be computed through multi-class traffic assignment. It should be noted that the traffic volume by modes can be changed according to the volume of empty vehicle travel because the link travel time determined by the traffic assignment is influenced by the traffic volume by modes. Therefore, it is necessary to repeat the procedure of modal split reflecting the updated link travel time due to the influence of empty vehicle travel. To this end, the process of multi-class traffic assignment and modal split are repeated until the total network travel time converges. The algorithms for multi-class assignment is the same as presented in chapter 4.2.1.



[Figure 4-5] Algorithm procedure in modal spilt and assignment considering empty vehicle travel

4.2.4. Calculation of Fitness Index (FI)

FI is an objective function of the upper model of the model, and it consists of the sum of TTC and OC. TTC of post-implementation can be calculated using on the link travel time and OD trips by modes through modal split and traffic assignment considering empty vehicle travel. OC is obtained through total DRAV fleet, the number of depot and capacity of each depot ($S_{cap,k}$) from the chromosome, and service level constraint of each depot from the modal split and assignment considering empty vehicle travel. And if the capacity of a certain depot is lower than its service level constraint, a big penalty is imposed to FI to exclude from the solution set. Finally, FI can be computed using TTC of pre-implementation calculated in base situation analysis with TTC and OC of post-implementation explained above. The calculation of FI of each chromosome is repeated for all chromosome in population set. The optimal solution in the generation based on FI is saved for evaluating termination condition in next step.



[Figure 4-6] Algorithm procedure in calculation of FI

4.2.5. Termination condition and updating population set

The optimal solution of the generation is evaluated to determine whether the algorithm end or not. In this study, the algorithm is set to terminate when the same optimal solution is repeated five times. Also, maximum generation is set to 50 that means the termination condition is set so that the evaluation of the optimal solution can be performed up to 50 generations.

If the termination condition is not satisfied, the population set is updated for next generation. Survival, crossover and mutation operations are performed, and the detail of each is explained as follows.

1) Survival

The first step of updating population set is to decide which chromosomes in the previous generation survive. To do that, all chromosomes in population set are sorted based on the FI. Then, the high ranked chromosomes are survived according to given survival rate. They are later used as parent chromosomes in selection and crossover procedure.

2) Selection

The selection in GA is an operation for selecting two parent chromosomes used for crossover. There are a variety of selection operations, but a common principle is that the probability of a good solution being chosen is high. In this study, the pattern of searching solution set varies greatly according to the number of the depot, and this can result in several local optima. For example, if the number of depots installed is one, it is possibly located at the hub node of the network, whereas depots may be located at two nodes outside of the network where demand is high in case of the number of the installed depot is two. Therefore, in this study, the survived chromosomes with the same number of depots are grouped, and the parent chromosomes in the same group are selected to generate the offspring chromosomes.

A Rank-based selection method that gives a selection probability in a linear function according to the quality of the surviving solution is adopted as a selection method in this study. This method increases the probability that a chromosome with a good fit is selected as a parent chromosome, thereby constructing an efficient algorithm. This model includes a large penalty in the calculation of the FI. Therefore, it is not appropriate to apply roulette wheel method which is based on the objective expression value itself or tournament method which selects parent chromosome based on the competition of two arbitrarily chosen chromosomes.

3) Crossover

In this study, the method for crossover is based on the point crossover. However, parent chromosomes within the same group by the number of the depot produce the offspring chromosomes having the same number of the depot to consider the possibility of several local optima as mentioned in the selection operation. The number of descendant chromosomes generated in each group is determined by the proportion of each group in the survival group. The table below shows the example of the offspring generation in crossover operation.

<Table 4-1> Example of offspring generation in crossover

Category	# of depots : 5	# of depots : 6	# of depots : 7	Total
# of survived chromosomes in parent generation	6	9	15	30
# of survived chromosomes in offspring generation	12	21	50	70
Proportion	20%	30%	50%	100%

4) Mutation

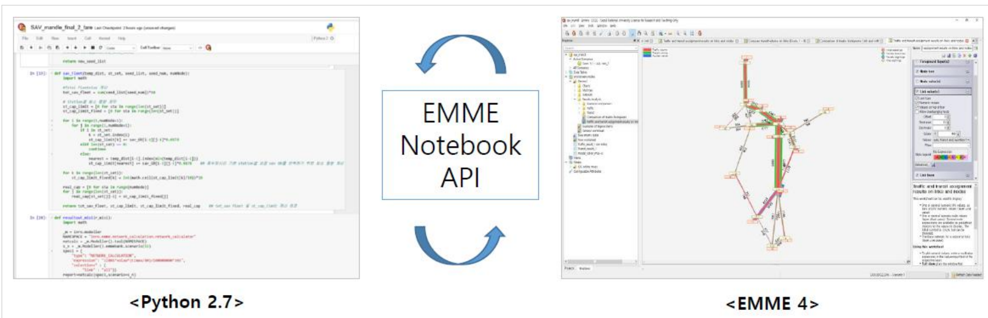
The mutation operation is used to search the global solution rather than the local solution by expanding the search space of the solution by introducing an attribute that does not exist in the parent chromosomes. In the algorithm of this study, the mutation operation is performed by converting the bit of the corresponding gene with 0 to 1 (or 1 to 0) according to a predetermined mutation rate among the newly generated descendants after crossover operation. This study needs to apply a value higher than the threshold values of a typical mutation operation (0.15, 0.1, etc.), because there may be various local optima. Since the calibration procedure for the optimal mutation threshold is most influenced by the network size, the mutation threshold setting in this study is discussed in detail in the case study section.

4.3. Algorithm Implementation

EMME 4.23 and Python 2.7 are used to implement the GA-based algorithm developed in this study. The EMME program is a typical traffic assignment commercial program used in transportation planning and can be linked with Python through the in-program Notebook API.

Generating initial population, computing empty vehicle travel of DRAV and depot capacity constraint, and general GA operations are made by coding in Python 2.7. Besides, base situation analysis, calculation of link travel time and volume by modes, calculation of FI are conducted through EMME 4.23.

In the present study, thousands of iterations are needed to find out optimal solutions repeating computation of upper and lower level model. Therefore, all processes concerning bi-level modeling are coded automatically using EMME 4 and Python.



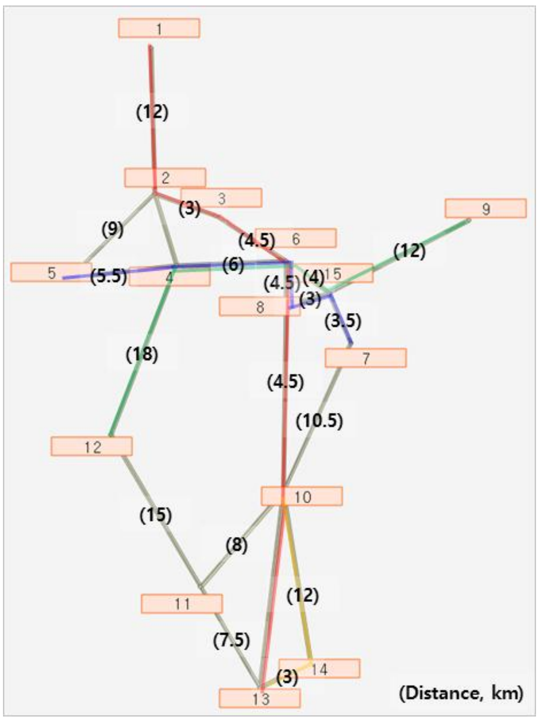
[Figure 4-7] Tools for algorithm implementation

5. Analysis Result

5.1. Case Study

5.1.1. Toy Network Summary

To verify the models and algorithms developed in this study, Mandl's network is set up as a toy network. The total length of the network is 159 km, and the routes for bus line consists of four as shown in the figure below. The vehicle speed is set to 60km/h for auto and DRAV, and 30km/h for the bus under the assumption of the urban network. The outline of Mandl's network is as follows.



[Figure 5-1] Mandl's Network

<Table 5-1> Configuration of Mandl's network

Category	Zone	Node	Link	Bus line
Mandl's Network	14	15	44	4

<Table 5-2> Bus line of Mandl's network

Bus line	Bus route
Line 1 (red)	1 → 2 → 3 → 6 → 8 → 10 → 13
Line 2 (blue)	5 → 4 → 6 → 8 → 15 → 7
Line 3 (green)	12 → 4 → 6 → 15 → 9
Line 4 (yellow)	10 → 14 → 13

The total OD volume in the analysis is 65,394 trips per day, and the intra-zonal trip is not considered. The areas with high trip generation are the zones 6 and 10, which are the top and central areas of the network. The areas with low trip generation are the zones 5, 9, 12, and 14, which are outside the network.

OD	1	2	3	4	5	6	7	8	9	10	11	12	13	14	계
1	0	1,680	840	252	336	630	315	315	126	672	126	105	147	0	**5,544**
2	1,680	0	210	504	84	756	378	378	63	546	84	42	42	21	**4,788**
3	840	210	0	168	252	756	378	378	63	189	84	42	42	21	**3,423**
4	252	504	168	0	210	420	210	210	63	1,008	168	105	42	21	**3,381**
5	336	84	252	210	0	210	105	105	42	504	84	63	21	0	**2,016**
6	630	756	756	420	210	0	420	420	126	3,696	252	63	63	42	**7,854**
7	315	378	378	210	105	420	0	210	63	1,848	147	42	42	21	**4,179**
8	315	378	378	210	105	420	210	0	63	1,848	147	42	42	21	**4,179**
9	126	63	63	63	42	126	63	63	0	588	84	21	0	0	**1,302**
10	672	546	189	1,008	504	3,696	1,848	1,848	588	0	2,520	1,050	2,100	840	**17,409**
11	126	84	84	168	84	252	147	147	84	2,520	0	315	399	63	**4,473**
12	105	42	42	105	63	63	42	42	21	1,050	315	0	294	0	**2,184**
13	147	42	42	42	21	63	42	42	0	2,100	399	294	0	189	**3,423**
14	0	21	21	21	0	42	21	21	0	840	63	0	189	0	**1,239**
계	**5,544**	**4,788**	**3,423**	**3,381**	**2,016**	**7,854**	**4,179**	**4,179**	**1,302**	**17,409**	**4,473**	**2,184**	**3,423**	**1,239**	**65,394**

[Figure 5-2] OD trip of the present study

5.1.2. GA Design Parameter Test

It is important to determine appropriate GA design parameters according to the network size and the range of feasible solutions. In applying Mandl's network to the model, main parameters such as the population size, the survival rate, and the mutation rate are tested.

1) Population size

The population size is the size of a solution set that is generated for each generation. If the population size is small, there is a risk that it will take a long time to analyze it because it is likely to fall into local optima in the first generation. In case of this study, it is crucial to determine the population size because of the wide range of the feasible solution and the existence of the various local solutions. The parameter test is performed based on whether the optimal solution is searched and the average time taken with a population size of 50~200. In all cases, the optimal solution is found, but the population size of 150 is the most appropriate regarding the average analysis time.

<Table 5-3> Result of population size test

Population size	Time per each generation	Average number of generation	Average analysis time(min.)
50	10.51	62	651.54
100	17.69	30	530.83
150	**28.58**	**18**	**514.41**
200	43.22	15	648.25

2) Survival rate

The survival rate in this study is similar to the crossover rate in the GA algorithm. It means the probability of surviving the chromosome of the good fitness in the generation for generating offspring chromosomes through crossover in next generation. If the survival rate is too low, it can survive a lot of chromosomes with good fitness in the initial population, but there is a danger of falling into the local solution. On the contrary, if the survival rate is too high, the number of newly generated chromosomes in the next generation may be small, and the analysis may take a long time or the search for the optimal solution may fail depending on the termination condition. The survival rate analysis shows that the lower the survival rate, the less average analysis time is required. Therefore 0.2 is set to the survival rate in the case study.

<Table 5-4> Result of survival rate test

Survival rate	Time per each generation	Average number of generation	Average analysis time(min.)
0.1	Occurrence of failure of finding global optima		
0.2	**28.58**	**18**	**514.41**
0.3	28.57	19	542.99
0.4	28.61	23	658.03

3) Mutation rate

The mutation rate can reduce the probability of falling into the local optima by giving different characteristic that is not found in the parent chromosome. In particular, this study has a problem of existence of various local optima that the pattern of the optimal solution varies depending on the location because the quantity and location of the depot are determined at the same time. Therefore, the parameter test for mutation rate is performed with higher values than the parameter value used in the general study. The mutation rate of 0.3 appears to the most efficient regarding the average analysis time.

<Table 5-5> Result of mutation rate test

Population Size	Time per one generation	Average number of generation	Average analysis time(min.)
0.1	28.51	29	826.77
0.2	28.67	21	602.14
0.3	**28.58**	**18**	**514.41**
0.4	28.63	19	543.99

5.1.3. Verification of Algorithm Performance

The algorithm of this study has a structure to determine the location, quantity, and capacity of the DRAV depot at the same time. This structure determines the location selection and allocation at the selected location at the same time. To verify the adequacy of this structure, the algorithm of this study is compared with the algorithm to determine the capacity of the depot after determining the location of the depot. The compared algorithm consists of two stages of GA. The location is determined in the first state. In the second stage, the optimal capacity of the depot is determined according to the depot location. Then, the fitness index is calculated, and the algorithm is terminated with the same termination condition as the model of this study. As a result of the analysis, the fitness index and the optimal solution (depot location, quantity, and capacity) are the same both cases. However, the algorithm of this model is found to be efficient regarding the average analysis time.

<Table 5-6> Result of mutation rate test

Category	Algorithm of the present study	Comparison Algorithm
Algorithm structure	One stage GA structure - Determining depot location, quantity, and capacity at the same time	Two stage GA structure - Allocating capacity after determining depot location and quantity
Composition of chromosome	Location, quantity, and capacity the depot	Step 1 : Location and quantity of depot Step 2 : Capacity of depot
Fitness Index (100 million won)	57.44	57.44
Time per one generation	28.58 minutes (about 0.5 hours)	1,089.62 minutes (about 18.16 hours)

5.1.4. Result of Case Study

1) Result of modal split

The network, OD and GA parameters presented above are used to determine the location, quantity, and capacity of the depot. First, user's behavior of mode choice after introducing DRAV is analyzed. The values of utility function coefficients, mode-specific constant, vehicle occupants and value of time for each mode in the manual of the preliminary feasibility study in Korea are referred for the analysis of modal split. For the DRAV, the value of the taxi with the most similar driving characteristics is applied, and the average value of passenger cars and buses are applied to the ratio of work and non-work trips.

As a result of the modal split, the share of auto and bus are 70% and 30% before DRAV system introduction, respectively, but the share of auto, bus, and DRAV after the system introduction appear to 59%, 25%, and 16% respectively. The amount of OD trips of auto shifted to DRAV is about three times higher than that of the bus, but the ratio of conversion rate is somewhat higher in the bus than auto. Also, due to the high number of the vehicle occupant in DRAV, traffic volume decreases by 1,298 (pcu/day) after DRAV introduction.

<Table 5-7> Modal split result of case study

Category			Auto	Bus	DRAV	Total
Pre[1]	OD	Trip(trip/day)	46,079	19,315	-	65,394
		Ratio	70.5%	29.5%	-	100.0%
	Traffic(pcu/day)		35,999	3,686	-	39,685
Post[2]	OD	Trip(trip/day)	38,319	16,454	10,621	65,394
		Ratio	58.6%	25.2%	16.2%	100.0%
	DRAV	Shifted trip	-7,760	-2,861	10,621	-
		Shifted ratio	16.8%	14.8%	-	-
	Traffic(pcu/day)		29,937	3,140	5,310	38,387

1) Pre : The situation before DRAV is implemented
2) Post : The situation after DRAV is implemented

As a result of analyzing the changes in modal share in post-implementation, the use of DRAV is relatively high in OD trips with zone 11 where not directly connected to the bus routes. This suggests the possibility of introducing DRAV as a new transportation mode for improving in vulnerable mobility areas.

OD	1	2	3	4	5	6	7	8	9	10	11	12	13	14
1	0.0%	14.2%	15.1%	19.7%	22.8%	16.3%	20.5%	16.3%	24.1%	14.5%	47.7%	30.8%	21.2%	0.0%
2	14.2%	0.0%	11.7%	14.2%	16.6%	12.9%	16.6%	13.5%	20.2%	13.4%	37.0%	23.7%	20.4%	18.1%
3	15.1%	11.7%	0.0%	14.4%	16.9%	12.1%	15.5%	12.6%	19.0%	13.2%	38.8%	23.1%	16.6%	18.5%
4	19.7%	14.2%	14.4%	0.0%	12.8%	12.2%	15.0%	12.9%	18.1%	14.7%	33.6%	17.1%	24.0%	21.4%
5	22.8%	16.6%	16.9%	12.8%	0.0%	14.6%	17.5%	15.2%	22.4%	17.4%	38.7%	21.1%	27.9%	0.0%
6	16.3%	12.9%	12.1%	12.2%	14.6%	0.0%	13.1%	11.2%	16.2%	12.6%	28.3%	19.1%	16.3%	17.8%
7	21.1%	16.8%	15.7%	15.3%	17.5%	13.3%	0.0%	12.6%	16.8%	16.6%	23.8%	23.1%	24.1%	23.4%
8	16.3%	13.5%	12.6%	12.9%	15.2%	11.2%	12.6%	0.0%	17.2%	12.4%	25.3%	20.5%	16.5%	17.6%
9	24.1%	20.2%	19.0%	18.1%	22.4%	16.2%	16.8%	17.2%	0.0%	22.1%	35.1%	25.5%	0.0%	0.0%
10	14.5%	13.4%	13.2%	14.7%	17.4%	12.6%	16.6%	12.4%	22.1%	0.0%	17.0%	24.7%	15.5%	14.8%
11	47.7%	37.0%	38.8%	33.6%	38.7%	28.3%	23.8%	25.3%	35.1%	17.0%	0.0%	21.0%	16.7%	18.3%
12	30.8%	23.7%	23.1%	17.1%	21.1%	19.1%	23.1%	20.5%	25.5%	24.7%	21.0%	0.0%	25.7%	0.0%
13	21.2%	20.4%	16.6%	24.0%	27.9%	16.3%	24.1%	16.5%	0.0%	15.5%	16.7%	25.7%	0.0%	11.8%
14	0.0%	18.1%	18.5%	21.4%	0.0%	17.8%	23.4%	17.6%	0.0%	14.8%	18.3%	0.0%	11.8%	0.0%

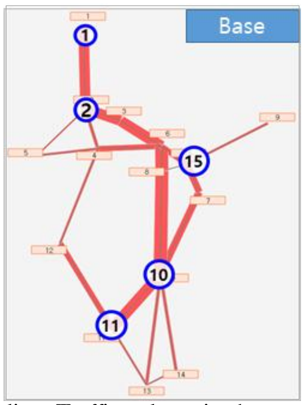
[Figure 5-3] Modal ratio of DRAV by OD in case study

2) Result of location and capacity of DRAV depot

The results of analyzing the location, quantity, and capacity of the optimal depot using the above situation as a base scenario are as follows.

<Table 5-8> Analysis result of case study

Category	Result					
The number of depot installed	5					
Total DRAV fleet size	250					
Depot capacity (Left: Zone, Right: Capacity)	#	Cap.	#	Cap.	#	Cap.
	1	30	6	-	11	60
	2	40	7	-	12	-
	3	-	8	-	13	-
	4	-	9	-	14	-
	5	-	10	60	15	60



*Red line: Traffic volume in the network
*Circle size: The capacity of depot

The optimal number of depots is analyzed to 5, and the total

DRAV fleet size is 250. The optimal capacity of each depot is analyzed as 30 at zone 1, 40 at zone 2, and 60 at zone 10, 11 and 15. The installed depot is located at the nodes with the high demand of DRAV such as zone 1 and 10. Moreover, the depot is installed around links with heavy traffic such as link 1-2 and 10-11.

The results also show that there is a trade-off between the travel time cost and the operator cost in the objective function since it is shown that depot does not installed at all nodes or does not installed in the minimum quantity by DRAV demand. From this, it can be deduced that the public institution needs to consider the cost of both user and operator side in the planning stage for depot installation.

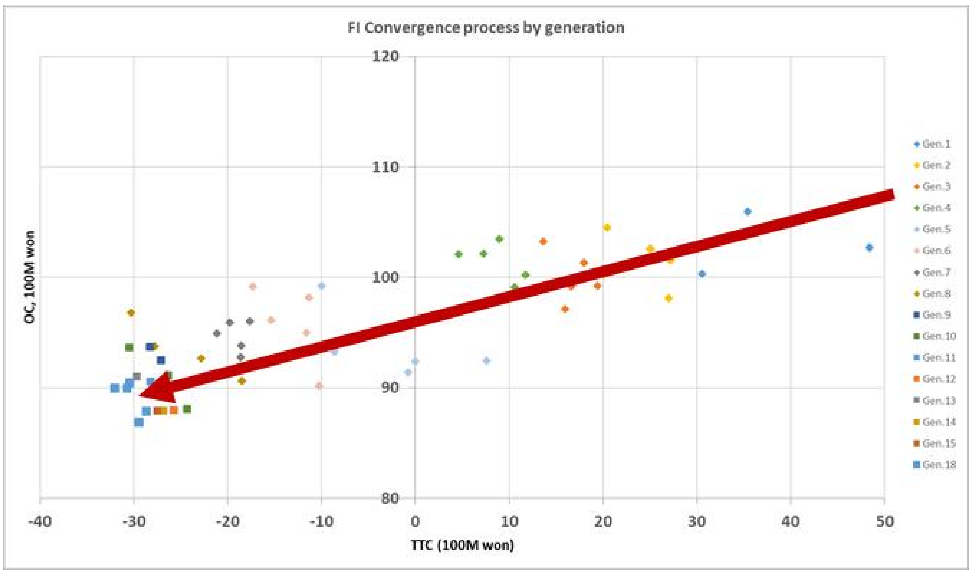
As a result FI, it shows the larger decrease in TTC than OC. From this, it can be seen that the influence of the TTC due to the empty vehicle travel of DRAV and modal share of each mode in post-implementation is greater than the annual cost required to introduce the DRAV system. This result is also confirmed in the process of convergence of FI by generations. It appears that FI converges to the direction of decreasing TTC compared to UC as shown below. This result implies that the network congestion cost due to the installation of depot should be considered in the process of determining depot location.

<Table 5-9> FI of case study

(Unit: 100 million won)

Gen. no.[1)]	Dep. quan.[2)]	Dep. cap.[3)]	TTC				UC	FI (TC)
			Auto	Bus	DRAV	Total		
1	4	400	-78.12	-36.12	144.81	30.58	100.31	130.88
2	4	380	-80.33	-36.46	143.81	27.02	98.14	125.15
3	4	370	-88.54	-37.51	142.01	15.95	97.13	113.08
4	6	360	-98.72	-36.18	139.53	4.64	102.11	106.75
5	5	310	-106.36	-38.29	136.03	-8.62	93.28	84.66
6	4	310	-107.16	-39.63	136.58	-10.21	90.2	79.99
7	5	330	-115.23	-39.98	134.07	-21.15	94.93	73.79
8	5	320	-119.44	-41.34	132.53	-28.24	93.73	65.49
9	4	320	-118.61	-42.15	132.54	-28.22	90.57	62.35
10	5	260	-115.99	-42.99	133.24	-25.74	87.97	62.23
11	5	260	-116.59	-43.76	132.86	-27.49	87.91	60.42
…								
18	5	250	-114.97	-46.97	132.49	-29.44	86.88	57.44

1) Gen. no.: Generation number
2) Dep. quan.: The quantity of depot installed
3) Dep. cap.: The capacity of depot (Total DRAV Fleet size)



[Figure 5-4] FI convergence process by generation in case study

5.2. Scenario Analysis

5.2.1. Scenario Configuration

The purpose of the scenario analysis is to analyze how the location, quantity, and capacity of the depot change according to various changes in the traffic situation in the future, and to derive meaningful implications by comparing with the result of the case study. For this purpose, the situation in the case study is set to base scenario. The summary of scenario configuration is presented as shown in the below table.

<Table 5-10> Summary of scenario analysis

No.	Title	Analysis purpose	Changes compared to base scenario
1	Congested situation	• To compare results under network congestion	• Increase total OD volume by 50%
2	OD trip pattern (Case 1)	• To compare results when OD trips between the outer zones in the network is high	• Increase OD trips of the outer zones (5, 9, 12, 13, 14)
3	OD trip pattern (Case 2)	• To compare results when OD trips are concentrated in a certain area	• Increase OD trips of the upper zones (1, 2, 3, 4, 5)
4	Vehicle Occupant	• To compare results assumption of ride sharing is not adopted	• Change the vehicle occupants of DRAV to that of taxi (2 → 1.54)
5	Fare	• To compare results by the change of DRAV fare due to government support	• Discount the fare of DRAV by 10~30%
6	Land cost	• To compare results deploying different land cost by depot candidates	• Apply 3 level of land cost based on the OD trips
7	Weighting on social cost	• To compare results with weighting on TTC considering benefit of public side	• Apply the weight of the TTC in objective function to 3 times of OC

5.2.2. Congested Situation Scenario

In congested situation scenario, the amount of each OD trips for all modes are increases by 50% compared to base scenario.

1) Result of modal split

Due to the increased total OD trips, the trips of DRAV increases by 3,222 (trips/day) to 13,843 (trips/day) compared with the base scenario. And the ratio of modal share for DRAV is analyzed 14.1%, which is decreased by 2.1% than base scenario. In congestion scenarios, modal share of transit increases compared with the base scenario, but the share of auto and DRAV decreases. This is because the travel cost of auto and DRAV increases with travel time, but bus fare is independent of travel time. Lastly, total traffic in the network is appeared to increase by 13,957 (pcu/day) compared to base scenario.

<Table 5-11> Modal split result of congestion scenario

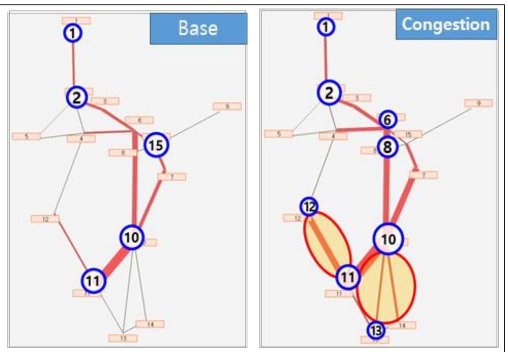
Category				Auto	Bus	DRAV	Total
Pre	Base	OD trip(trip/day)		46,079	19,315	-	65,394
		Traffic(pcu/day)		35,999	3,686	-	39,685
	Cong.[1]	OD trip(trip/day)		59,282	38,809	-	98,091
		Traffic(pcu/day)		46,314	7,406	-	53,721
Post	Base	OD	Trip(trip/day)	38,319	16,454	10,621	65,394
			Ratio	58.60%	25.20%	16.20%	100.00%
		DRAV	Shifted trip	-7,760	-2,861	10,621	-
			Shifted ratio	16.80%	14.80%	-	-
		Traffic(pcu/day)		29,937	3,140	5,310	38,387
	Cong.	OD	Trip(trip/day)	49,703	34,545	13,843	98,091
			Ratio	50.70%	35.20%	14.10%	100.00%
		DRAV	Shifted trip	-9,580	-4,264	13,843	-
			Shifted ratio	16.20%	11.00%	-	-
		Traffic(pcu/day)		38,830	6,593	6,922	52,344

1) Cong. : Congestion scenario

2) Result of location and capacity of DRAV depot

The number of depots installed reveals to 8 which is increased by 3 compared to base scenario. The newly installed depots are located in the zone around the links with heavy traffic or at the zone with high DRAV demand. It is interpreted that the depot is installed in the areas where the congestion is greatly increased because TTC increases exponentially as congestion gets worse. That is, the depot is installed in the areas where the increase of TTC due to congestion is minimized while inducing the decrease of empty AV vehicle. Moreover, total DRAV fleet size is analyzed to 360, which is increased by 110 than base scenario due to the increase in DRAV demand. Since the capacity of each depot is decided by total AV fleet size per each depot, total DRAV fleet size can be calculated by the sum of the capacity of installed depots.

<Table 5-12> Analysis result of congestion scenario

<table>
<tr><td>Category</td><td colspan="6">Result</td><td rowspan="9">

*Red line: Traffic volume in the network
*Circle size: The capacity of depot</td></tr>
<tr><td>The number of depot installed</td><td colspan="6">8</td></tr>
<tr><td>Total DRAV fleet size</td><td colspan="6">360</td></tr>
<tr><td rowspan="6">Depot capacity
(Left: Node, Right: Capacity)</td><td>#</td><td>Cap.</td><td>#</td><td>Cap.</td><td>#</td><td>Cap.</td></tr>
<tr><td>1</td><td>30</td><td>6</td><td>30</td><td>11</td><td>50</td></tr>
<tr><td>2</td><td>60</td><td>7</td><td>-</td><td>12</td><td>30</td></tr>
<tr><td>3</td><td>-</td><td>8</td><td>50</td><td>13</td><td>30</td></tr>
<tr><td>4</td><td>-</td><td>9</td><td>-</td><td>14</td><td>-</td></tr>
<tr><td>5</td><td>-</td><td>10</td><td>80</td><td>15</td><td>-</td></tr>
</table>

As a result of FI, TTC decreases by 18.9 (100 million won/year). This means that the influence in the decrease in TTC due to changing transport modes to DRAV is greater than that in the increase in TTC due to empty vehicle travel of DRAV in congested situation scenario compared to base scenario. Besides, OC increases by 7.5 (100 million won/year) due to the increase of both depot and service vehicle. Total cost (TC), which is the same as FI, increases by 20 (100 million won/year) than base scenario because the effect of the decrease in TTC is smaller than the increase in OC.

<Table 5-13> FI of congestion scenario

(Unit: 100 million won/year)

Category	Travel Time Cost				Operator Cost[1]						FI (TC)
	Auto	Bus	DRAV	Sum	OC1	OC2	OC3	OC4	OC5	Sum	
Base	-115.0	-47.0	132.5	-29.4	18.8	3.9	4.0	46.9	13.4	86.9	57.4
Cong.	-181.1	-67.8	200.6	-48.3	27.0	5.8	6.4	65.7	20.8	125.7	77.4
Difference[2]	-66.1	-20.9	68.1	-18.9	8.3	2.0	2.4	18.7	7.5	38.9	20.0

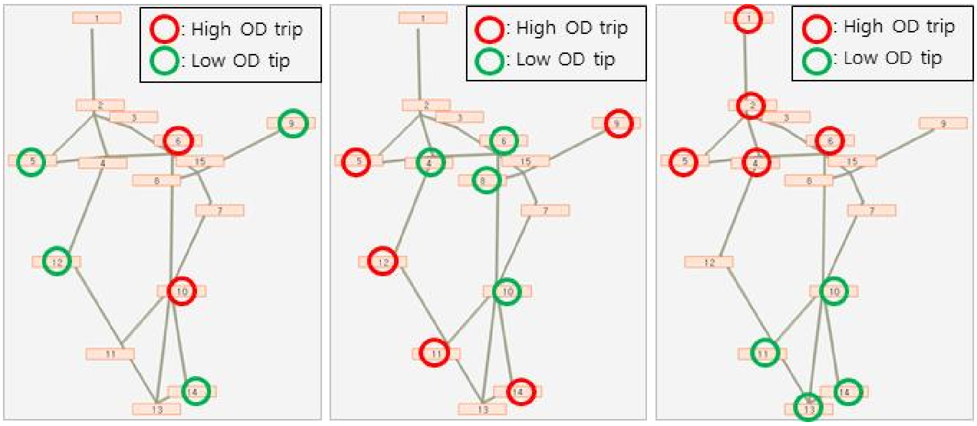
1) OC1: Purchase cost of vehicle, OC2: depot construction cost, OC3: Land and other fixed cost, OC4: DRAV operating cost, OC5: depot operating cost
2) Difference: Cong.-Base

5.2.3. OD Trip Pattern Scenario

The OD trip pattern scenario consists of two cases. Case 1 is to increase the number of long-distance traffic by increasing OD trips between the outer zones, and case 2 is to concentrate the traffic in a specific area to make congestion in that area extremely. The configuration of this scenario is shown following table and figure.

<Table 5-14> Configuration of OD trip pattern scenario

Scenario		Zones with high OD trip	
		Location	Zone number
Base		Central area	6, 10
Change in OD trip pattern	Case 1	Outer area	5, 9, 12, 13, 14
	Case 2	Upper area	1, 2, 3, 4, 5



[Figure 5-5] Configuration of OD patterns in Mandl's network

1) Result of modal split

The ratio of modal share for DRAV decreases by 2.1% in case 1, since the ratio of the share for bus increases due to the increase of long-distance trips. This is reasonable since travel cost of the bus is relatively low than other transport modes as travel distance increase. In case 2, modal share for DRAV also decreases by 1.1%, because travel time in upper areas, where many bus lines operate, increases rapidly, leading to the increase of the high share of the bus. Traffic volume in both cases appears to decrease by 8,482 and 1,859 (pcu/day) compared to base scenario due to the relatively high decrease of auto traffic volume.

<Table 5-15> Modal split result of OD pattern scenario

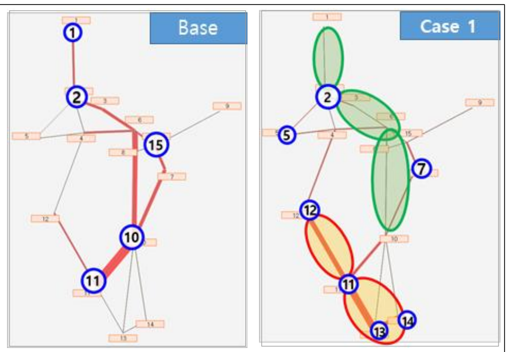
<table>
<tr><td colspan="4">Category</td><td>Auto</td><td>Bus</td><td>DRAV</td><td>Total</td></tr>
<tr><td rowspan="6">Pre</td><td rowspan="2">Base</td><td colspan="2">OD trip(trip/day)</td><td>46,079</td><td>19,315</td><td>-</td><td>65,394</td></tr>
<tr><td colspan="2">Traffic(pcu/day)</td><td>35,999</td><td>3,686</td><td>-</td><td>39,685</td></tr>
<tr><td rowspan="2">Case 1</td><td colspan="2">OD trip(trip/day)</td><td>31,018</td><td>34,376</td><td>-</td><td>65,394</td></tr>
<tr><td colspan="2">Traffic(pcu/day)</td><td>24,232</td><td>6,560</td><td>-</td><td>30,793</td></tr>
<tr><td rowspan="2">Case 2</td><td colspan="2">OD trip(trip/day)</td><td>42,113</td><td>23,281</td><td>-</td><td>65,394</td></tr>
<tr><td colspan="2">Traffic(pcu/day)</td><td>32,900</td><td>4,443</td><td>-</td><td>37,343</td></tr>
<tr><td rowspan="15">Post</td><td rowspan="5">Base</td><td rowspan="2">OD</td><td>Trip(trip/day)</td><td>38,319</td><td>16,454</td><td>10,621</td><td>65,394</td></tr>
<tr><td>Ratio</td><td>58.60%</td><td>25.20%</td><td>16.20%</td><td>100.00%</td></tr>
<tr><td rowspan="2">DRAV</td><td>Shifted trip</td><td>-7,760</td><td>-2,861</td><td>10,621</td><td>-</td></tr>
<tr><td>Shifted ratio</td><td>16.80%</td><td>14.80%</td><td>-</td><td>-</td></tr>
<tr><td colspan="2">Traffic(pcu/day)</td><td>29,937</td><td>3,140</td><td>5,310</td><td>38,387</td></tr>
<tr><td rowspan="5">Case 1</td><td rowspan="2">OD</td><td>Trip(trip/day)</td><td>24,677</td><td>31,478</td><td>9,239</td><td>65,394</td></tr>
<tr><td>Ratio</td><td>37.70%</td><td>48.10%</td><td>14.10%</td><td>100.00%</td></tr>
<tr><td rowspan="2">DRAV</td><td>Shifted trip</td><td>-6,341</td><td>-2,898</td><td>9,239</td><td>-</td></tr>
<tr><td>Shifted ratio</td><td>20.40%</td><td>8.40%</td><td>-</td><td>-</td></tr>
<tr><td colspan="2">Traffic(pcu/day)</td><td>19,279</td><td>6,007</td><td>4,620</td><td>29,906</td></tr>
<tr><td rowspan="5">Case 2</td><td rowspan="2">OD</td><td>Trip(trip/day)</td><td>35,561</td><td>19,958</td><td>9,876</td><td>65,394</td></tr>
<tr><td>Ratio</td><td>54.40%</td><td>30.50%</td><td>15.10%</td><td>100.00%</td></tr>
<tr><td rowspan="2">DRAV</td><td>Shifted trip</td><td>-6,552</td><td>-3,324</td><td>9,876</td><td>-</td></tr>
<tr><td>Shifted ratio</td><td>15.60%</td><td>14.30%</td><td>-</td><td>-</td></tr>
<tr><td colspan="2">Traffic(pcu/day)</td><td>27,782</td><td>3,809</td><td>4,938</td><td>36,528</td></tr>
</table>

2) Result of location and capacity of DRAV depot

As a result of the analysis in case 1, depots are installed at the outer zones due to large DRAV demand. Also, the depot at 15 is shifted to 7 since the congestion in the central road (1-2-6-8-10) decrease. In case 2, several small size depots are installed in the upper area where demand is high, and somewhat large depots installed at zone 4 and 8 to provide service to remaining areas. The number of depots installed is 7 in case 1, and 6 in case 2. The reasons to increase total fleet size in both cases despite the decrease of DRAV demand is that the average distance traveled increases in case 1 and travel time in a specific region largely increases in case 2. Therefore, the model to decide depot capacity not only by DRAV demand but also by user's travel distance (or travel time) can be verified. From these results, it can be concluded that the depot location of the DRAV depends on the traffic pattern of the introduction area, and it is necessary to reduce the TTC by installing a lot of depots when the congestion in a specific section is severe.

<Table 5-16> Analysis result of OD pattern scenario(Case 1)

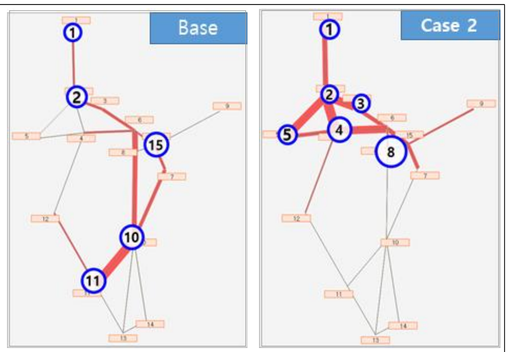
Category	Result					
The number of depot installed	7					
Total DRAV fleet size	270					
Depot capacity (Left: Node, Right: Capacity)	#	Cap.	#	Cap.	#	Cap.
	1	-	6	-	11	40
	2	60	7	40	12	40
	3	-	8	-	13	30
	4	-	9	-	14	30
	5	30	10	-	15	-



*Red line: Traffic volume in the network
*Circle size: The capacity of depot

<Table 5-17> Analysis result of OD pattern scenario(Case 2)

Category	Result					
The number of depot installed	6					
Total DRAV fleet size	280					
Depot capacity (Left: Node, Right: Capacity)	#	Cap.	#	Cap.	#	Cap.
	1	40	6	-	11	-
	2	30	7	-	12	-
	3	30	8	80	13	-
	4	60	9	-	14	-
	5	40	10	-	15	-



*Red line: Traffic volume in the network
*Circle size: The capacity of depot

As a result of FI, TTC in case 1 decreases by 40.0 (100 million won/year), whereas TTC in case 2 increases by 17.7 (100 million won/year). It means that the relative decrease in TTC due to changing transport modes to DRAV is greater than the increase in TTC due to empty AV travel in case 1 because a large number of auto trips is shifted to other transport modes. And the opposite result appears in case 2 due to the rapid increase of congestion cost which is determined by BPR function. From this result, a trade-off between total traffic flow reductions due to the differences of vehicle occupants of transport modes and DRAV traffic flow increases due to empty vehicle travel is confirmed. Besides, OC increases in both cases because more depots and service vehicles are required than base scenario. TC is analyzed to decrease by 20.7 (100 million won/year) in case 1 and increase by 21.6 (100 million won/year) in case 2.

<Table 5-18> FI of OD pattern scenario

(Unit: 100 million won/year)

Category		Travel Time Cost				Operator Cost						FI (TC)
		Auto	Bus	DRAV	Sum	OC1	OC2	OC3	OC4	OC5	Sum	
Base		-115.0	-47.0	132.5	-29.4	18.8	4.0	3.9	46.9	13.4	86.9	57.4
Case 1	Cost	-141.4	-79.0	151.1	-69.4	20.3	4.7	5.6	57.9	17.7	106.1	36.7
	Diff.	-26.5	-32.1	18.6	-40.0	1.5	0.9	1.6	11.0	4.3	19.2	-20.7
Case 2	Cost	-91.2	-56.7	136.1	-11.7	21.0	4.5	4.8	44.7	15.8	90.7	79.0
	Diff.	23.8	-9.7	3.6	17.7	2.3	0.6	0.8	-2.2	2.4	3.9	21.6

5.2.4. Vehicle Occupant Scenario

In the base scenario, vehicle occupant of AV is assumed to 2.0

under the assumption of activation of ride sharing when the DRAV system is introduced in future. In vehicle occupant scenario, the in-vehicle passenger of AV is set to 1.54, which is the current vehicle occupant of taxi provided from the manual of the preliminary feasibility in Korea.

1) Result of modal split

Since the price for using DRAV per person is increased by the decreased vehicle occupant, modal share of DRAV decreases by 5.9% (16.2% → 10.3%) compared with base scenario. Besides, total traffic increases by 1,436 (pcu/day) due to the decreased vehicle occupant of DRAV, which accompany the increase of AV traffic per shifted trips from other transport modes.

<Table 5-19> Modal split result of passenger occupant scenario

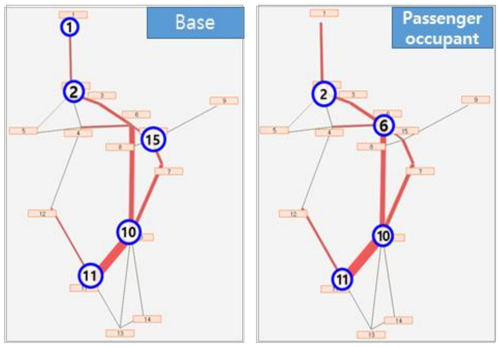
Category				Auto	Bus	DRAV	Total
Pre	Base	OD trip(trip/day)		46,079	19,315	-	65,394
		Traffic(pcu/day)		35,999	3,686	-	39,685
Post	Base	OD	Trip(trip/day)	38,319	16,454	10,621	65,394
			Ratio	58.60%	25.20%	16.20%	100.00%
		DRAV	Shifted trip	-7,760	-2,861	10,621	-
			Shifted ratio	16.80%	14.80%	-	-
		Traffic(pcu/day)		29,937	3,140	5,310	38,387
	Occu.[1)]	OD	Trip(trip/day)	41,060	17,571	6,763	65,394
			Ratio	62.80%	26.90%	10.30%	100.00%
		DRAV	Shifted trip	-5,019	-1,745	6,763	-
			Shifted ratio	10.90%	9.00%	-	-
		Traffic(pcu/day)		32,078	3,353	3,382	38,813

1) Occu. : Passenger occupant scenario

2) Result of location and capacity of DRAV depot

The number of depots installed and total fleet size of DRAV appears to 4 and 220 respectively, which are decreased by 1 and 30 compared to base scenario because of decrease of DRAV demand. Depots installed at zone 1 and 2 in the base scenario are merged into zone 2 in this scenario due to the reduction of demand. Moreover, the depot at node 15 in base scenario reveals to be shifted to zone 6, where road congestion is high because the effect of TTC reduction is large in the congested area by installing depot.

<Table 5-20> Analysis result of vehicle occupant scenario

<table>
<tr><td>Category</td><td colspan="6">Result</td><td rowspan="9">

*Red line: Traffic volume in the network
*Circle size: The capacity of depot</td></tr>
<tr><td>The number of depot installed</td><td colspan="6">4</td></tr>
<tr><td>Total DRAV fleet size</td><td colspan="6">220</td></tr>
<tr><td rowspan="6">Depot capacity

(Left: Node, Right: Capacity)</td><td>#</td><td>Cap.</td><td>#</td><td>Cap.</td><td>#</td><td>Cap.</td></tr>
<tr><td>1</td><td>-</td><td>6</td><td>50</td><td>11</td><td>60</td></tr>
<tr><td>2</td><td>70</td><td>7</td><td>-</td><td>12</td><td>-</td></tr>
<tr><td>3</td><td>-</td><td>8</td><td>-</td><td>13</td><td>-</td></tr>
<tr><td>4</td><td>-</td><td>9</td><td>-</td><td>14</td><td>-</td></tr>
<tr><td>5</td><td>-</td><td>10</td><td>50</td><td>15</td><td>-</td></tr>
</table>

Regarding the FI, TTC is analyzed to have positive value unlike that of other scenarios due to the low shifted volume to DRAV. Since TTC is affected by the difference of travel time by each mode in before and after implementation of DRAV system, the lower the number of trips being converted, the greater the TTC. In case of OC, 15.7 (100 million won/year) is decreased due to the reduction of depot and DRAV fleet size. And TC is analyzed to increase by 48 (100 million won/year) compared with base scenario because of more influence by TTC than OC.

<Table 5-21> FI of passenger occupant scenario

(Unit: 100 million won/year)

Category	Travel Time Cost				Operator Cost						FI (TC)
	Auto	Bus	DRAV	Sum	OC1	OC2	OC3	OC4	OC5	Sum	
Base	-115.0	-47.0	132.5	-29.4	18.8	4.0	3.9	46.9	13.4	86.9	57.4
Occu.	-47.1	-27.1	108.3	34.2	16.5	3.3	3.2	37.3	10.9	71.2	105.4
Diff.	67.9	19.9	-24.2	63.6	-2.3	-0.6	-0.8	-9.6	-2.4	-15.7	47.9

5.2.5. Fare Scenario

As presented in several previous studies, ride sharing can create a variety of social benefits, which can be further enhanced by using AV. Therefore, when DRAV system is introduced, public sector organizations can promote activation policies such as rate discount. Therefore, the change of depot location and capacity when the fare is discounted by 10%, 20%, and 30% are analyzed.

1) Result of modal split

As a result of fare analyses, the share of DRAV increases by 2~3% as the fare is reduced by 10% (16.2% → 18.8% → 21.6% → 24.6%). Moreover the trips shifted from other transport modes to DRAV increases by 2,000 (trips/day) by every 10% discount of fare (10,621 → 12,266 → 14,095 → 16,101). Although the shifted trips to DARV are high in all scenarios concerning fare, total traffic in these scenarios are similar to that in the base scenario. This is because that more bus trips are shifted to DRAV as fare discount rate increases compared to base scenario. From this point of view, it can be seen that DRAV can have great competitiveness in public transportation if a high rate discount is applied.

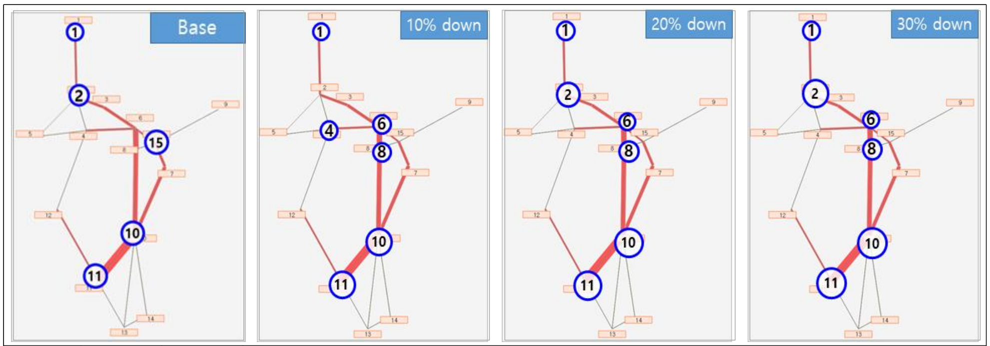
<Table 5-22> Modal split result of fare scenario

Category				Auto	Bus	DRAV	Total
Pre	Base	OD trip(trip/day)		46,079	19,315	-	65,394
		Traffic(pcu/day)		35,999	3,686	-	39,685
Post	Base	OD	Trip(trip/day)	38,319	16,454	10,621	65,394
			Ratio	58.60%	25.20%	16.20%	100.00%
		DRAV	Shifted trip	-7,760	-2,861	10,621	-
			Shifted ratio	16.80%	14.80%	-	-
		Traffic(pcu/day)		29,937	3,140	5,310	38,387
	10% down	OD	Trip(trip/day)	37,169	15,959	12,266	65,394
			Ratio	56.80%	24.40%	18.80%	100.00%
		DRAV	Shifted trip	-8,910	-3,356	12,266	-
			Shifted ratio	19.30%	17.40%	-	-
		Traffic(pcu/day)		29,038	3,046	6,133	38,217
	20% down	OD	Trip(trip/day)	35,902	15,397	14,095	65,394
			Ratio	54.90%	23.50%	21.60%	100.00%
		DRAV	Shifted trip	-10,177	-3,918	14,095	-
			Shifted ratio	22.10%	20.30%	-	-
		Traffic(pcu/day)		28,048	2,938	7,047	38,034
	30% down	OD	Trip(trip/day)	34,523	14,770	16,101	65,394
			Ratio	52.80%	22.60%	24.60%	100.00%
		DRAV	Shifted trip	-11,555	-4,545	16,101	-
			Shifted ratio	25.10%	23.50%	-	-
		Traffic(pcu/day)		26,971	2,819	8,050	37,840

2) Result of location and capacity of DRAV depot

The number of depots installed is analyzed to increase by 1 in all discounting cases due to the increase in demand, and depot location at node 15 is shifted to zone 6 and 8 separately. This means that depot is located in areas where the impact of road congestion due to empty vehicle travel can be largely reduced if DRAV demand increases significantly. Therefore, this result is reasonable since there are high OD trips of DRAV at zone 6 and 8, and node 15 is not transportation zone. Lastly, total AV fleet size increases as the fare is lower even though road congestion is similar to that in the base scenario.

<Table 5-23> Analysis result of fare scenario



Cate-gory	Total DI[1]	Total FS[2]	Depot capacity															
			#	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15
Base	5	250	Cap.	30	40	-	-	-	-	-	-	-	60	60	-	-	-	60
10%	6	290		30	-	-	40	-	40	-	40	-	70	70	-	-	-	-
20%	6	340		40	60	-	-	-	30	-	50	-	80	80	-	-	-	-
30%	6	370		40	70	-	-	-	30	-	50	-	90	90	-	-	-	-

1) Total DI: The number of depot installed
2) Total FS: Total DRAV fleet size
※ 10% (20%, 30%) stands for 10% (20%, 30%) discount of DRAV fare

As a result of FI, TTC decreases by 6.9~17.2 (100 million won/year) as fare discount rate increases. This means that the impact of the decrease in TTC due to changing transport modes to DRAV is greater than that of increase in TTC due to empty vehicle travel of DRAV in fare scenario compared to base scenario. On the other hand, OC increases by 15.1~41.9 (100 million won/year) due to the increase of both depot and service vehicles. TC increases by 8.2~24.7 (100 million won/year) compared with base scenario because the effect of the increase in OC is larger than that of the decrease in TTC.

<Table 5-24> FI of fare scenario

(Unit: 100 million won/year)

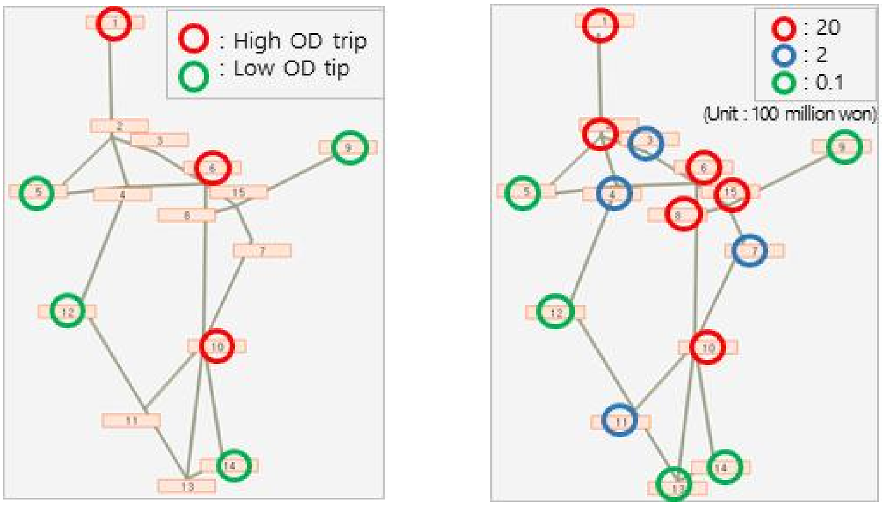
Category		Travel Time Cost				Operator Cost						FI (TC)
		Auto	Bus	DRAV	Sum	OC1	OC2	OC3	OC4	OC5	Sum	
Base		-115.0	-47.0	132.5	-29.4	18.8	4.0	3.9	46.9	13.4	86.9	57.4
10% down	Cost	-135.2	-56.0	154.9	-36.4	21.8	4.6	4.8	55.0	15.9	102.0	65.6
	Diff.	-20.2	-9.1	22.4	-6.9	3.0	0.7	0.8	8.1	2.5	15.1	8.2
20% down	Cost	-156.0	-66.4	180.3	-42.1	25.5	5.0	4.8	64.1	16.5	115.9	73.8
	Diff.	-41.0	-19.4	47.8	-12.7	6.8	1.1	0.8	17.2	3.2	29.0	16.3
30% down	Cost	-177.3	-78.0	208.7	-46.6	27.8	5.3	4.8	74.1	16.9	128.8	82.2
	Diff.	-62.4	-31.0	76.2	-17.2	9.0	1.4	0.8	27.2	3.6	41.9	24.7

5.2.6. Land Cost Scenario

In the base scenario, land cost of all depot candidates is set to same. In reality, however, land costs vary depending on land use and surrounding infrastructure. Therefore, different land cost by depot candidates is set to find out the change of the depot decision. In this scenario, there are three types of land costs according to the number of trips generated as shown below.

<Table 5-25> Configuration of OD trip pattern scenario

Land cost (100 million won)	Candidates for depot location zone
20	1, 2, 6, 8, 10, 15
2	3, 4, 7, 11
0.1	5, 9, 12, 13, 14



[Figure 5-6] Configuration of land cost by depot candidates(right) based on trip pattern(left)

1) Result of modal split

Since there is no change in the volume and pattern of OD trips, as well as some critical factors affecting modal split such as vehicle occupant and fare, there is minute change on the modal split in land cost scenario compared to base scenario. The change of travel time by empty vehicle travel is the only factor to influence on the modal split in this scenario. Accordingly, the traffic volume also dose not change much.

<Table 5-26> Modal split result of landcost scenario

Category				Auto	Bus	DRAV	Total
Pre	Base	OD trip(trip/day)		46,079	19,315	-	65,394
		Traffic(pcu/day)		35,999	3,686	-	39,685
Post	Base	OD	Trip(trip/day)	38,319	16,454	10,621	65,394
			Ratio	58.60%	25.20%	16.20%	100.00%
		DRAV	Shifted trip	-7,760	-2,861	10,621	-
			Shifted ratio	16.80%	14.80%	-	-
		Traffic(pcu/day)		29,937	3,140	5,310	38,387
	Land.[1]	OD	Trip(trip/day)	38,198	16,607	10,589	65,394
			Ratio	58.40%	25.40%	16.20%	100.00%
		DRAV	Shifted trip	-7,881	-2,708	10,589	-
			Shifted ratio	17.10%	14.00%	-	-
		Traffic(pcu/day)		29,842	3,169	5,295	38,306

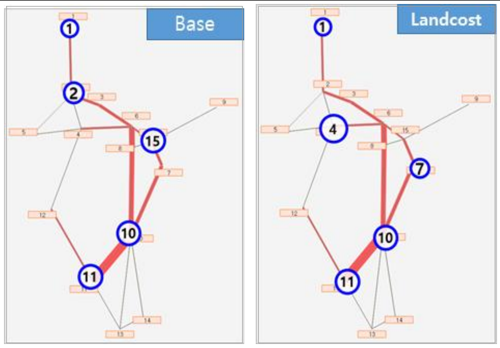
1) Land. : Land cost scenario

2) Result of location and capacity of DRAV depot

As a result of analysis of DRAV depot decision, the total number of depot installed is same, but some changes appeares concerning the location of depots compared to base scenario. Depot at zone 2 shifts to zone 4, and depot at node 15 moved to zone 7. From this result, it is inferred that the depot installed in the low demand area is changed to the area with low land cost, whereas the depot in the high demand still installed at the same place in the base scenario. Therefore, the trade-off between TTC and UC has confirmed again in this scenario. Total fleet size of DRAV increases a little due to the small increase in travel distance.

<Table 5-27> Analysis result of land cost scenario

Category	Result					
The number of depot installed	5					
Total DRAV fleet size	260					
Depot capacity (Left: Node, Right: Capacity)	#	Cap.	#	Cap.	#	Cap.
	1	30	6	–	11	60
	2	–	7	40	12	–
	3	–	8	–	13	–
	4	70	9	–	14	–
	5	–	10	60	15	–



*Red line: Traffic volume in the network
*Circle size: The capacity of depot

The comparison of FI is meaningless because the cost of all depots varies greatly compared to the base scenario. Therefore, the interpretation of the analysis results is omitted.

5.2.7. Weighting on Social Cost Scenario

The model developed in this study aims to be used in public institution. Therefore it can be valuable for decision makers to force more on social cost than monetary cost. Thus, the change in the location, quantity, and capacity of depot is analyzed by weighting on TTC, which is social cost of user side, by 3 times of OC in this scenario.

1) Result of modal split

As the result of land cost scenario, there is no significant change in the modal split, because there is no change concerning OD, vehicle occupant and the fare of DRAV. Accordingly, trips of each transport modes and the total traffic volume does not change much.

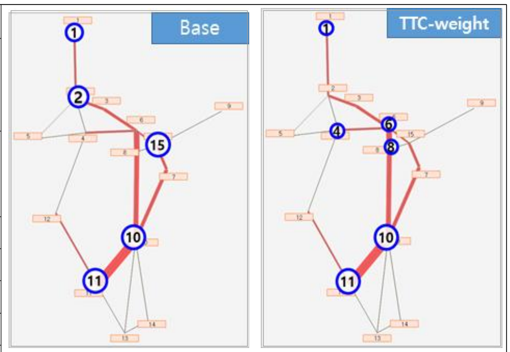
<Table 5-28> Modal split result of TTC-weight scenario

Category				Auto	Bus	DRAV	Total
Pre	Base	OD trip(trip/day)		46,079	19,315	-	65,394
		Traffic(pcu/day)		35,999	3,686	-	39,685
Post	Base	OD	Trip(trip/day)	38,319	16,454	10,621	65,394
			Ratio	58.60%	25.20%	16.20%	100.00%
		DRAV	Shifted trip	-7,760	-2,861	10,621	-
			Shifted ratio	16.80%	14.80%	-	-
		Traffic(pcu/day)		29,937	3,140	5,310	38,387
	TTC.[1)]	OD	Trip(trip/day)	38,258	16,531	10,605	65,394
			Ratio	58.50%	25.30%	16.20%	100.00%
		DRAV	Shifted trip	-7,820	-2,785	10,605	-
			Shifted ratio	17.00%	14.40%	-	-
		Traffic(pcu/day)		29,889	3,155	5,302	38,347

1) TTC. : TTC-weight scenario

2) Result of location and capacity of DRAV depot

<Table 5-29> Analysis result of TTC-weight scenario

<table>
<tr><td>Category</td><td colspan="6">Result</td><td rowspan="9">

*Red line: Traffic volume in the network
*Circle size: The capacity of depot</td></tr>
<tr><td>The number of depot installed</td><td colspan="6">6</td></tr>
<tr><td>Total DRAV fleet size</td><td colspan="6">250</td></tr>
<tr><td rowspan="6">Depot capacity
(Left: Node, Right: Capacity)</td><td>#</td><td>Cap.</td><td>#</td><td>Cap.</td><td>#</td><td>Cap.</td></tr>
<tr><td>1</td><td>30</td><td>6</td><td>30</td><td>11</td><td>60</td></tr>
<tr><td>2</td><td>-</td><td>7</td><td>-</td><td>12</td><td>-</td></tr>
<tr><td>3</td><td>-</td><td>8</td><td>40</td><td>13</td><td>-</td></tr>
<tr><td>4</td><td>30</td><td>9</td><td>-</td><td>14</td><td>-</td></tr>
<tr><td>5</td><td>-</td><td>10</td><td>60</td><td>15</td><td>-</td></tr>
</table>

The number of depots installed increases by 1 and depots installed at zone 2 and node 15 in the base scenario is shifted to zone 4, 6 and 8 in this scenario. In other words, several small depots are installed around the congested area to reduce TTC caused by empty AV travel as shown in case 2 of OD trip pattern scenario. Since there is no social cost in OC, it appears better to install more depots to decrease TTC.

As a result of FI, TTC decreases significantly due to the effect of weighting. Although there is the small increase in OC by the additional installation of the depot, TC also reduces by 63.6 (100 million won/year) because of the large decrease of TTC.

<Table 5-30> FI of TTC-weight scenario

(Unit: 100 million won/year)

Cate-gory	Travel Time Cost				Operator Cost						FI (TC)
	Auto	Bus	DRAV	Sum	OC1	OC2	OC3	OC4	OC5	Sum	
Base	-115.0	-47.0	132.5	-29.4	18.8	4.0	3.9	46.9	13.4	86.9	57.4
TTC.	-351.1	-140.9	395.9	-96.1	18.8	4.2	4.8	46.9	15.4	90.0	-6.2
Diff.	-236.1	-94.0	263.4	-66.7	-	0.3	0.8	-0.1	2.0	3.1	-63.6

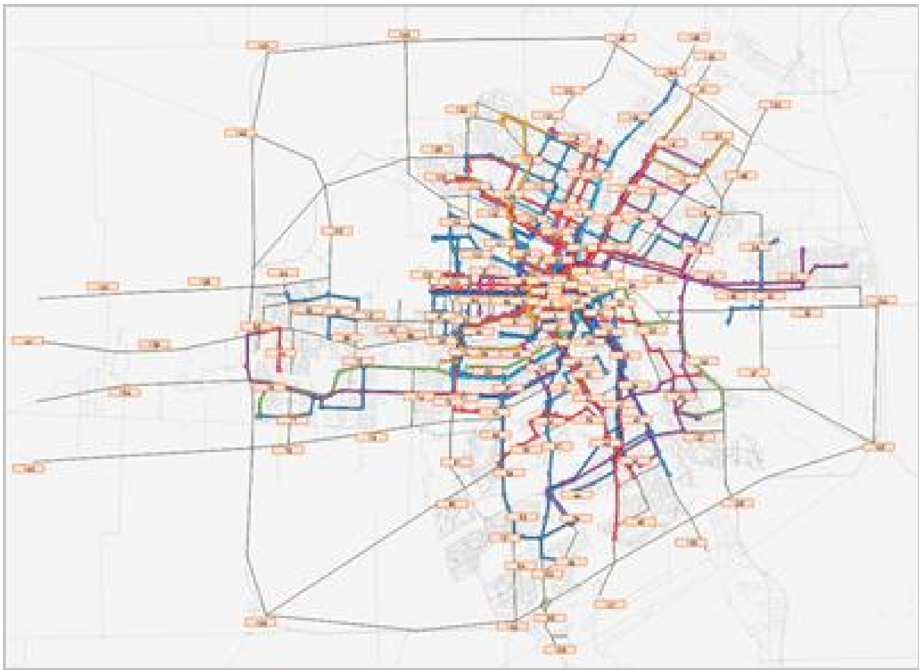
5.3. Large-scale Network Analysis

5.3.1. Summary of Large-scale Network

To confirm the practical applicability of the model and algorithm developed in this study, large-scale network analysis is performed. Winnipeg network, which widely used in network analysis, is adopted for large-scale network analysis. Daily OD trips for each transport modes are constructed, and the number of for depot candidates location is set to 80. The configuration of the depot is present as follows.

<Table 5-31> Summary of Winnipeg network

Zone	Node	Link	Bus line	# of depot candidates	Total NW length(km)	Total OD (trip/day)
147	893	2,238	62	80	694	181,675



[Figure 5-7] Winnipeg network configuration

Some constraints and GA design parameters are changed for efficient large-scale network analysis. First of all, the maximum depot capacity constraint is changed from 150 to 300, because the total OD trip is increased compared to the case study. To achieve this, twenty times the value of the individual gene in the chromosome is set to represent the capacity of the depot. For example, a gene value of 1 means that the depot capacity is 20, and a gene value of 9 means that the depot capacity is 180. Moreover, the population size is set to 3,000 in the first generation, and it is changed to 500 from the second generation. Since the size of the solution set increases exponentially due to the increase of depot candidates in large-scale network analysis, the search for the initial solution is important.

5.3.2. Results of Large-scale Network Analysis

1) Result of modal split

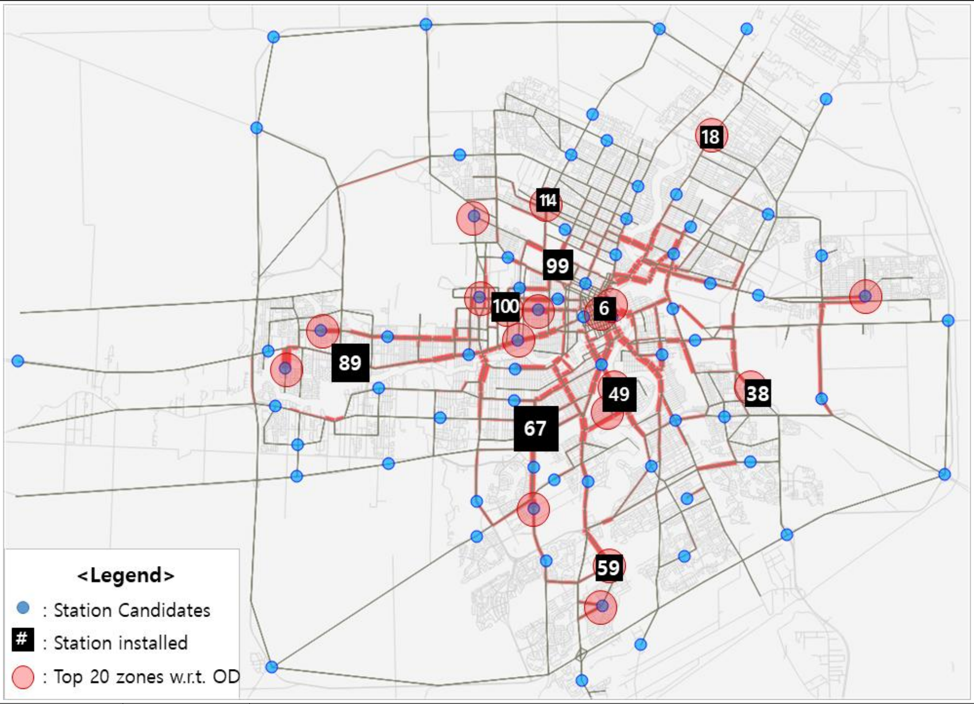
As a result of the modal split, modal share of auto and bus appears to 78.7% and 21.3% respectively in pre-implementation of DRAV system. After the system is implemented the share of auto, bus, and DRAV are change to 67.2%, 18.3%, and 14.4%. Also, total traffic decreases by 4,049 (pcu/day), which is 3.4% of reduction by the introduction of DRAV system.

<Table 5-32> Modal split result of large-scale network

Category			Auto	Bus	DRAV	Total
Pre	OD	Trip(trip/day)	142,952	38,723	-	181,675
		Ratio	78.70%	21.30%	-	100.00%
	Traffic(pcu/day)		111,682	7,390	-	119,071
Post	OD	Trip(trip/day)	122,159	33,272	26,244	181,675
		Ratio	67.20%	18.30%	14.40%	100.00%
	DRAV	Shifted trip	-7,760	-2,861	10,621	-
		Shifted ratio	14.60%	14.10%	-	-
	Traffic(pcu/day)		95,550	6,350	13,122	115,022

2) Result of location and capacity of DRAV depot

<Table 5-33> Analysis result of large-scale network



Total DI[1)]	Total FS[2)]	Depot capacity										
		Node	6	18	38	49	59	67	89	99	100	114
10	800	Cap.	40	40	60	120	120	180	120	80	60	40

1) Total DI: The number of depot installed
2) Total FS: Total DRAV fleet size

The optimal number of depots is analyzed to 10, and the total DRAV fleet size is 8,000. The optimal capacity of each depot is analyzed as 40 at zone 6, 18 and 114, and 60 at zone 38 and 100, and 80 at zone 99, and 120 at zone 49, 59, and 89, and 180 at zone 67. This result is reasonable because the location of the determined depots is installed in the high demand nodes and the nodes around the link where high traffic volume occurs, as in the case analysis result.

The optimal solution converges through the calculation of 44 generations. Since the variation of TTC is larger than the variation of OC, as in case study, the optimal solution is analyzed to reduce the TTC by decreasing empty vehicle travel.

<Table 5-34> FI of Winnipeg network

(Unit: 100 million won/year)

Gen. no.[1)]	Dep. no.[2)]	Dep. cap.[3)]	TTC				OC	FI (TC)
			Auto	Bus	DRAV	Total		
1	10	1160	164.58	-35.4	295.55	424.74	217.59	642.33
2	12	1040	43.2	-59.94	284.96	268.21	207.58	475.79
3	10	920	-74.09	-72.67	276.01	129.25	194.08	323.34
4	10	1000	-96.92	-77.01	274.45	100.52	201.3	301.82
5	9	870	-120.04	-78.14	272.19	74.01	185.65	259.66
6	10	810	-133.74	-75.08	270.88	62.06	182.74	244.8
7	10	960	-166.28	-85.24	268.45	16.92	196.88	213.81
8	11	960	-167.8	-87	268.33	13.54	197.68	211.22
9	10	800	-145.16	-77.52	270.25	47.57	181.74	229.31
10	10	950	-178.81	-87.45	267.57	1.31	195.89	197.2
11	10	960	-184.14	-89.53	267.16	-6.51	196.78	190.28
12	10	960	-184.14	-89.53	267.16	-6.51	196.78	190.28
…								
44	10	800	-197.94	-97.08	268.57	-26.45	180.59	154.14

1) Gen. no. : Generation number
2) Dep. no. : The number of depot installed
3) Dep. cap. : The capacity of depot (Total DRAV Fleet size)

6. Conclusion

6.1. Summary and Conclusion

Various future transport service has been suggested with the rapid development of AV and shared mobility-related technologies. According to this development, research and technology developments for SAV, a one-way car-sharing service using AV, are in progress in the private sectors. On the contrary, there is still insufficient consideration of AV-related transport services in the public domain. Transport services using AV can generate several social benefits such as travel convenience for users in the blind spot of transport mobility and the decrease in energy and emissions. Therefore, this study constructs a model and solution algorithm to determine the optimal location, quantity, and capacity of the depot, when public institutions provide DRAV system.

In the model construction process, TTC as social costs of users and UC as monetary costs of the operator are considered simultaneously. Road congestion costs due to empty AV travel, overlooked in the previous studies, are considered for TTC calculations. In this study, bi-level model is applied to calculate the network travel time that varies depending on depot location. Especially, modal split and multi-class traffic assignment (UE for auto and DRAV, and optimal strategy for the bus) considering empty vehicle travel, are iteratively conducted to represent more realistic travel behavior according to depot locations. The GA based meta-heuristic algorithm is developed to solve the problems in this study. Characteristics of this study, solution pattern depends on the number of depots, are considered in the algorithm development process.

The developed models and algorithms are applied to Mandl's network to perform the case study. From the case study, it appears that there is a trade-off between TTC and OC. Installation of depot reduces TTC with decreased empty travel of DRAC, while operation costs of depot installation and management are increased.

Following conclusions can be derived from various scenario analyses. First, depot locations for DRAV system are determined at congested areas according to traffic patterns in the target area. Additionally, a trade-off is existed between total traffic flow reductions due to the differences of vehicle occupants of transport modes, and DRAV traffic flow increases due to empty vehicle travel. Furthermore, if an area had comparatively lower DRAV demand but the higher land price, then depot location is alternatively selected at the lower priced area. If social costs considering public purpose have higher weights, it is determined to install more depots to minimize TTC due to empty vehicle travel. Lastly, results of large network analysis appears reasonably, hence, it can be confirmed that developed model and algorithm in this study is applicable for the real world problems.

Policy implications from the analysis in this study are as follows.

First, influencing factors for the depot location selections such as local transport environment and location-related factors (e.g. traffic volume, travel pattern, public transport route, land price) should be fully considered at the planning stage of DRAV depot. Second, when a DRAV activation policy such as fare discount is implemented, it is necessary to accompanied by a road congestion management policy such as ride sharing for offsetting the additional traffic due to empty AV travel. Lastly, the decision maker of metropolitan areas where the congestion impact is high needs to install the sufficient number of small-sized depots within the available budget range to efficient road management.

6.2. Further Research

The limitations of the present study and further researches to improve this research are as follows.

First, this study determines the optimal location, quantity, and capacity of depot under the condition that DRAV system introduced. As several studies state that the on-demand transport service using AV will be implemented in the near future, feasibility studies on the introduction of the DRAV system within the specific area will be required. In this process, qualitative advantages of AV usage, not considered in this study, can be taken account. For example, service AV in the system could provide more comfortable travel for vulnerable road users (e.g, disabled, elderly, and pregnant). DRAV can also be utilized as a para-transit to improve accessibilities in the blind spot of transport service provision. Additionally, AV would contribute significantly to traffic safety because more than 90% of current accidents are caused by human factors. Therefore, feasibilities of the adopting DRAV system in considering both quantitative and qualitative advantages of AV can be conducted in further studies.

Second, this study covers a static problem which determines the location of the depot in the planning level. Therefore operation side of the DRAV service is not fully considered. Further studies can investigate various service operation strategies applying dynamic demand model. The operational strategy that an AV can move to next user without returning to the depot after the transport service can be a possible research example. Besides, vehicle relocation strategies can also be studied by using the information of waiting vehicles in all depots in the network.

Finally, transfer behavior between AV and existing transit is not considered in this study. Therefore, AV travel cannot be utilized as an approaching mode to transit in this study. However, on-demand service using AV is possible in the future when self-driving is active. Currently, there are several self-driving pilot tests, such as in Las Vegas and Pangyo, using automated shuttles in fixed short distance routes. These automated shuttles aim to be utilized an accessible mode of transit in the short-term. Therefore, it is necessary to study on location model to determine the on-demand AV station through the development of a model that reflects the transfer behavior between AV and transit.

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Appendix 1. Value of Time for DRAV

○ Average value of time by mode is calculated based on the value in the manual, and converted into the value of 2016 using consumer price index.

○ The ratio of trip purpose for DRAV is computed based on the average of the ratios of trip purpose for auto and bus.

<Average value of time per vehicle by mode (Daejeon in 2007)>

구분	Auto		Bus		DRAV	
	Work	Non-work	Work	Non-work	Work	Non-work
Ratio of trip purpose(%)	8.42	91.58	1.14	98.86	4.78	95.22
Vehicle occupant (peo.)	0.15	1.13	1.11	9.37	0.10	1.90
Value of time (won)	22,775	9,748	17,260 (1 person) 22,775 (0.15 person)	5,011	22,775	9,748
Value of time (won/veh*hour)	3,364	11,038	12,241	46,953	2,177	18,564
Average value of time in 2007 (won/veh)	14,401		59,194		20,741	
Average value of time in 2016 (won/veh)	14,838		60,987		21,370	

Source: The manual of the preliminary feasibility study in Korea (2007)

Appendix 2. OD Data for Trip Pattern Scenario

1. Case 1

OD	1	2	3	4	5	6	7	8	9	10	11	12	13	14	Total
1	0	308	308	31	615	31	308	31	615	31	308	615	615	615	4,429
2	308	0	308	31	615	31	308	31	615	31	308	615	615	615	4,429
3	308	308	0	31	615	31	308	31	615	31	308	615	615	615	4,429
4	31	31	31	0	62	15	31	15	62	15	31	62	62	62	508
5	615	615	615	62	0	62	615	62	1,230	62	615	1,230	1,230	1,230	8,243
6	31	31	31	15	62	0	31	15	62	15	31	62	62	62	508
7	308	308	308	31	615	31	0	31	615	31	308	615	615	615	4,429
8	31	31	31	15	62	15	31	0	62	15	31	62	62	62	508
9	615	615	615	62	1,230	62	615	62	0	62	615	1,230	1,230	1,230	8,243
10	31	31	31	15	62	15	31	15	62	0	31	62	62	62	508
11	308	308	308	31	615	31	308	31	615	31	0	615	615	615	4,429
12	615	615	615	62	1,230	62	615	62	1,230	62	615	0	1,230	1,230	8,243
13	615	615	615	62	1,230	62	615	62	1,230	62	615	1,230	0	1,230	8,243
14	615	615	615	62	1,230	62	615	62	1,230	62	615	1,230	1,230	0	8,243
15	4,429	4,429	4,429	508	8,243	508	4,429	508	8,243	508	4,429	8,243	8,243	8,243	65,394

2. Case 2

OD	1	2	3	4	5	6	7	8	9	10	11	12	13	14	Total
1	0	1,014	1,521	1,521	1,521	507	507	507	507	51	51	507	51	0	8,263
2	1,014	0	1,521	1,521	1,521	507	507	507	507	51	51	507	51	51	8,314
3	1,521	1,521	0	1,521	1,521	507	507	507	507	51	51	507	51	51	8,821
4	1,521	1,521	1,521	0	1,521	507	507	507	507	51	51	507	51	51	8,821
5	1,521	1,521	1,521	1,521	0	507	507	507	507	51	51	507	51	0	8,770
6	507	507	507	507	507	0	507	507	507	30	30	304	30	30	4,481
7	507	507	507	507	507	507	0	507	507	30	30	304	30	30	4,481
8	507	507	507	507	507	507	507	0	507	30	30	30	30	30	4,208
9	507	507	507	507	507	507	507	507	0	30	30	30	0	0	4,147
10	51	51	51	51	51	30	30	30	30	0	30	30	30	30	497
11	51	51	51	51	51	30	30	30	30	30	0	30	30	30	497
12	507	507	507	507	507	304	304	30	30	30	30	0	30	0	3,295
13	51	51	51	51	51	30	30	30	0	30	30	30	0	30	466
14	0	51	51	51	0	30	30	30	0	30	30	0	30	0	335
15	8,263	8,314	8,821	8,821	8,770	4,481	4,481	4,208	4,147	497	497	3,295	466	335	65,394

국문 초록

수요응답형 자율주행차의 Depot 입지 및 용량 결정

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미래의 자동차 및 교통 분야에서는 자율주행차 (AV: Autonomous Vehicle) 및 공유교통과 관련된 다양한 기술 고도화가 이루어지고 있다. 이에 수요대응형 교통 (DRT: Demand Responsive Transport) 분야에서도 AV를 활용한 One-way 카쉐어링 서비스인 공유형 자율주행차 (SAV: Shared Autonomous Vehicle) 등의 다양한 서비스가 제시되고 있다. 수요대응형 자율주행차 (DRAV: Demand Responsive Autonomous Vehicle) 시스템은 공공영역에서의 on-demand 서비스에 AV를 활용한 시스템으로, 이는 교통 사각지대 이용자 및 교통약자들의 이동편의를 향상 및 Ride Sharing과 연계한 수요관리 정책으로써도 활용이 가능하여 새로운 준 대중교통수단으로써의 경쟁력이 있다. 하지만 많은 연구에서 다수의 AV의 공차통행으로 인한 도로혼잡을 우려하고 있지만, 현재까지는 이를 반영한 연구가 부족한 실정이다. DRAV depot의 설치는 AV의 공차운행으로 인한 도로혼잡을 최소화 할 뿐 아니라 차량의 효율적인 관리, 미래형 이차전지 자동차의 충전소 등의 다양한 역할을 할 수 있다.

이에 본 연구에서는 DRAV depot의 최적 입지, 수량 및 용량을 결정

하는 모형 및 알고리즘을 개발하는 것을 그 목적으로 한다. 모형에서는 서비스를 위해 이용수요의 기종점과 depot 간 발생하는 공차통행을 고려한 네트워크 혼잡을 반영하고, 반복적인 수단분담 및 통행배정 절차를 포함하여 보다 현실적인 이용자의 통행행태를 반영하였다. 또한 NP-hard의 문제를 합리적인 시간 내에 풀이하기 위해 GA 기반의 알고리즘을 개발하였으며, depot 개수에 따라 해의 패턴이 달라지는 본 문제의 특성을 알고리즘 내에 반영하였다. 효율적인 분석을 위하여 대표적인 교통망 시뮬레이션 프로그램인 EMME4를 활용하였으며, Application programming interface (API)로 Python 2.7을 활용해 완전 자동화 풀이가 가능하도록 구현하였다.

Mandl’s 네트워크를 대상으로 case study 분석 결과 DRAV depot의 결정 과정에서 공차운행으로 인한 네트워크 혼잡비용을 반영한 분석의 필요성 확인되었다. Depot 입지 및 용량 결정은 기본적으로 이용수요가 많은 곳을 중심으로 발생되지만 혼잡이 심한 구간에서는 추가적인 depot의 건설을 통해 혼잡비용을 더 줄이는 것이 효과적으로 나타났다. 또한 미래의 다양한 상황에 대한 시나리오 분석으로부터 depot 입지 선정 시 통행량, 통행패턴, 대중교통 노선, 지가 등 입지 선정에 영향을 미칠 수 있는 요인들에 대한 다각적인 검토가 필요함을 입증하였다. 마지막으로 대규모 네트워크 분석에서도 개발된 모형 및 알고리즘이 합리적인 시간 내에 해를 도출하여, 본 연구의 현실적 활용성을 확인하였다.

주요어 : 수요응답형 자율주행차, Depot 입지 및 용량 결정모형,
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